TAMPEREEN TEKNILLINEN YLIOPISTO
TAMPERE UNIVERSITY OF TECHNOLOGY

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OPTIMIZING DEMAND PLANNING PROCESS – SEEKING THE BEST STATISTICAL FORECASTING METHOD

Master of Science Thesis

Examiners: Professor Paul H. Andersson and Professor Juho Kanniainen
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ABSTRACT

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Companies are increasingly looking to plan their business more cost-effectively. Statistical forecasting has been deeply involved in the planning process to form a fact-based planning process. The purpose of statistical forecasting is to maintain and improve the current level of service, which affect the lead times. Forecasting allows companies to coordinate their production so that delivery times meet the demand. The case company has begun to use the Sales and Operations Planning process to help improve the company's business. The purpose of this thesis is to develop the above-mentioned process of finding the best possible statistical forecasting technique and categorize the case company's products in such way that they can be used for demand forecasting. The literature review will present several of statistical forecasting techniques and a technique which can be used to categorize the case company's products. One of the purposes of the literature review is to give the reader a clear picture of how the supply chain, and Sales and Operations Planning are linked. The literature review works as a reference to find the best possible forecasting method for the case company's data. Additionally, the literature review presents a categorization technique, which will categorize the case company's products by their data's variability and monetary importance. Based on aforementioned findings recommendations are made to aid Sales and Operations Planning Demand planning process.

The thesis discovered that the data analysis is particularly important. In the analysis it became clear how much the data have variation as well as whether there exist the seasonal variation in the data and trends. The results showed that the data had a seasonal variation and trends. According to the findings, after the comparison of the forecasting methods, the most suitable statistical forecasting method was found – Holt's – Winters'. Based on the research, forecast accuracy can be improved by using X- categorized products having a low volatility. The study also looked for a correlation between the case company and the global industry indexes. According to the results, there was a positive or a negative trend with one month delay with a certain probability. The last task was to create a quality control for demand planning and forecasting. The purpose of the quality control was to follow the demand plan accuracy and to create control limits and also to find out if the most suitable forecasting method of the forecast tests is not too sophisticated for the time series. Conducting the long term performance analysis the historical demand plans need to be stored and compared with the actual figures. For this reason, a waterfall analysis was created. The purpose was to compare the current and past demand plans with actual demand figures. The key idea was to find out what is the error percent between the demand plans and the actual demand for an each given month in Sales & Operations Planning eighteen-month time frame. To this end, a solution was formed by a waterfall analysis which follows actual figures and forecasted values.

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Yritykset haluavat yhä enemmän suunnitella toimintaansa kustannustehokkaasti. Ennustaminen on ollut vahvasti mukana suunniteltuprosessissa mahdollistamassa faktapohjaisen suunnitteluprosessin. Tavoitteena ennustamisella on ylläpitää ja parantaa nykyistä palvelutasoa, johon vaikuttavat toimitusajat. Ennustaminen mahdollistaa tuotannon koordinoinnin siten, että toimitusajat kohtaavat kysynnän kanssa. Kohdeyritys on alkanut käyttää integroitua myynnin ja toiminnan suunnitteluprosessia apuna parantamaan yrityksen toimintaa. Diplomityön tavoitteena on kehittää edellä mainittua prosessia löytämällä paras mahdollinen tilastollinen ennustetekniikka ja kategorisoida kohde yrityksen tuotteet siten, että niitä voidaan käyttää tehokkaammin kysynnän ennustamisessa. Kirjallisuustutkimuksessa tarkoituksena on esitellä erilaisia vaihtoehtoja tilastollisen ennustamistekniikan valintaan ja samalla löytää hyvä kategorisointitekniikka. Kirjallisuusosuuden tavoitteena on antaa lukijalle selvä kuva siitä, miten toimitusketju ja integroitu myynnin ja toiminnan suunnittelu ovat sidoksissa toisiinsa. Kirjallisuusosuuteen nojaten, kohde yritykselle löydetään paras mahdollinen tilastollinen ennustetekniikka ja kategorisoidaan tuotteet niiden ennustettavuuden ja rahallisen arvon perusteella sekä yhdistämällä tulokset integroidun myynnin ja toiminnan suunnitteluprosessiin suosittelemalla erilaisia etenemisvaihtoehtoja kysynnän suunnittelussa.
Tutkimuksessa selvisi, että ennustedatan analysointi on erityisen tärkeää. Analysoinnissa selvisi kuinka suuri datan heilunta on ajansuhteen sekä onko datassa kausivaihtelua ja trendejä. Tuloksissa ilmeni, että datassa on kausivaihtelua ja trendejä. Tukien löydöstä, kohdeyrityksen dataan löytyi ennustetekniikkavertailun jälkeen Holt-Winters ennustemetodi. Kirjallisuustutkimukseen nojaten, ennustetarkkuutta voitiin parantaa käyttämällä kategorisoituja X-tuotteita, joilla on matala tilastollinen heilunta. Tutkimuksessa etsittiin myös korrelaatiota kohdeyrityksen ja globaalien teollisuus indeksien välillä. Tuloksena oli kuukauden viiveellä oleva tietyllä todennäköisyydellä esiintyvä positiivinen tai negatiivinen trendi. Viimeiseksi tehtäväksi muodostui kysynnän suunnittelun ja tilastollisen ennustamisen laadun valvonta. Tarkoitus oli seurata kysynnän ennustamisen toteutumistarkkuutta sekä luoda kontrollirajapinnat ja selvittää onko ennusteanalyysin voittaja liian sofistikoitunut ennustemetodi kyseiselle aikasarjalle. Kysynnän ennustaminen pitkällä aikavälillä vaatii historiatietojen tallentamista ja niiden vertaamista toteumaan. Tästä syystä seurantaa varten luotiin vesiputousanalyysi, jonka tavoite oli vertailla nykyistä ja menneitä kysynnän suunnitelmia toteuman kanssa ja selvittää kuinka suuri on kysynnän suunnittelun prosentuaalinen virhe tietyn kuukauden kohdalla integroidun myynnin ja tuotannon kahdeksantoista kuukauden aikataulussa. Tämän tiedon avulla kohdeyrityksen toimintaa voidaan optimoida vielä lisää ymmärtämällä ja hallitsemalla odotettu ennustevirhe.

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LIST OF SYMBOLS AND ABBREVIATIONS

ATO	Assembly to Order
B2B	Business to Business
CEO	Chief Executive Officer
ETO	Engineer to Order
Ifo	Information und Forschung (GER) (Information and Research)
KPI	Key Performance Indicator
MA	Moving averages
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
MFE	Mean Forecast Error
MTO	Make to Order
MTS	Make to Stock
OECD	Organization for Economic Co-operation and Development
ROI	Return On Investment
RSFE	Running Sum of Forecast Errors
S&OP	Sales and Operations Planning
SCM	Supply Chain Management
SES	Single Exponential Smoothing
SR	Simple Regression

1 INTRODUCTION

This is a Master of Science Thesis done for a company operating in, among others, electrical motor industry. The main focus of this thesis is Sales and Operations Planning (S&OP) and demand planning processes which is part of S&OP. These two processes are linked to each other and make a powerful tool to evaluate and predict a certain business future. Purpose of sales forecasting processes is to satisfy customers and to develop business by giving customers their ordered product according to agreed schedule. Forecasting also gives an opportunity to adjust production and inventories into right levels. It enables companies to save money without making a significant investment.

Forecasting, in general, enables companies to adjust, for instance, factories to match the need of customers. Demand forecasting, however, is to recognize possible customers who is or is about to make an order. Therefore, when conducting business, it is important to be aware of the future. Since knowing the future and making right decisions before competitors, results to high profit income and permanent customers. Moreover, forecasting decreases costs, which are indicated by the lower inventory levels and optimized production. [1]

1.1 Scope and background of the Thesis

The scope of this thesis will be on Sales and Operations Planning focusing on Demand Planning in a global electrical motors business. Addition to aforementioned topics the case company's sales forecasting process will be the most important development target. The idea of this master thesis is to analyze, discover and improve forecasting methods in S&OP framework. The scope is limited to preselected case company's products and electrical motor business.

In all aspects of business, customer service is an important factor. The case company's common customer relationships are of the business to business (B2B) type. Therefore, customers rely on delivery times and may select business partners who can match their own schedule or pick the one who can sell desired products as soon as possible [2, p. 65]. There are several other objectives which can be optimized by using forecasts. For instance, inventory management can adjust stocks to match demand, capacity management can optimize productivity to avoid over and under production and receiving purchased materials form suppliers will improve if forecasts are shared with them. This leads to more accurate deliveries from supply side. This is why forecasting is required. Forecasting can cut lead time and give a competitive advantage for a company. All in all, the most important advantages of S&OP include possibilities to adjust manufacturing and balancing demand and supply.

The key reason why forecasting is needed is the need to increase competitiveness. Sustainable business needs to develop its functions, for instance inventory control. Typically huge inventories bids a lot of capital, therefore there is a need to cut inventories by using forecasting as an enabler part of S&OP. Forecasting enables companies to anticipate the future phenomena, which will result, for instance, a less capital consuming stock.

1.2 Purpose of the Thesis

The case company has decided to develop S&OP in order to make right and fact-based decisions for the future. Sales and Operations Planning consists of constant communication between factories, sales units and high decision makers. S&OP informs decision makers what is the current and future demand and what the capacity of producing by a factory is. [3, p. 8]

Since the global S&OP is new in the case company, the experience of Sales and Operations Planning is small and most of the research of this thesis is based on firsthand experience. Nevertheless, the challenges which the case company is facing include how to make a solid S&OP process. Since, Sales and Operations Planning is new in the case company, this research needs to create and evaluate findings constantly.

The case company presented three research questions for this Thesis which need to be solved during this thesis. The questions are as follows:

- How to analyze and categorize and forecast different products in the case company's business globally?
- How to link abovementioned into the S&OP framework?
- How to utilize further for operations?

1.3 Research method of the Thesis

The theory section holds the literature review and makes a solid base for the thesis. The literature review part will use several research materials such as professional literature and university study material. The idea is to create an easily understandable holistic combination for the empirical part of this thesis. Literature review chapters will follow constantly the same research pattern showed in figure 1.1.

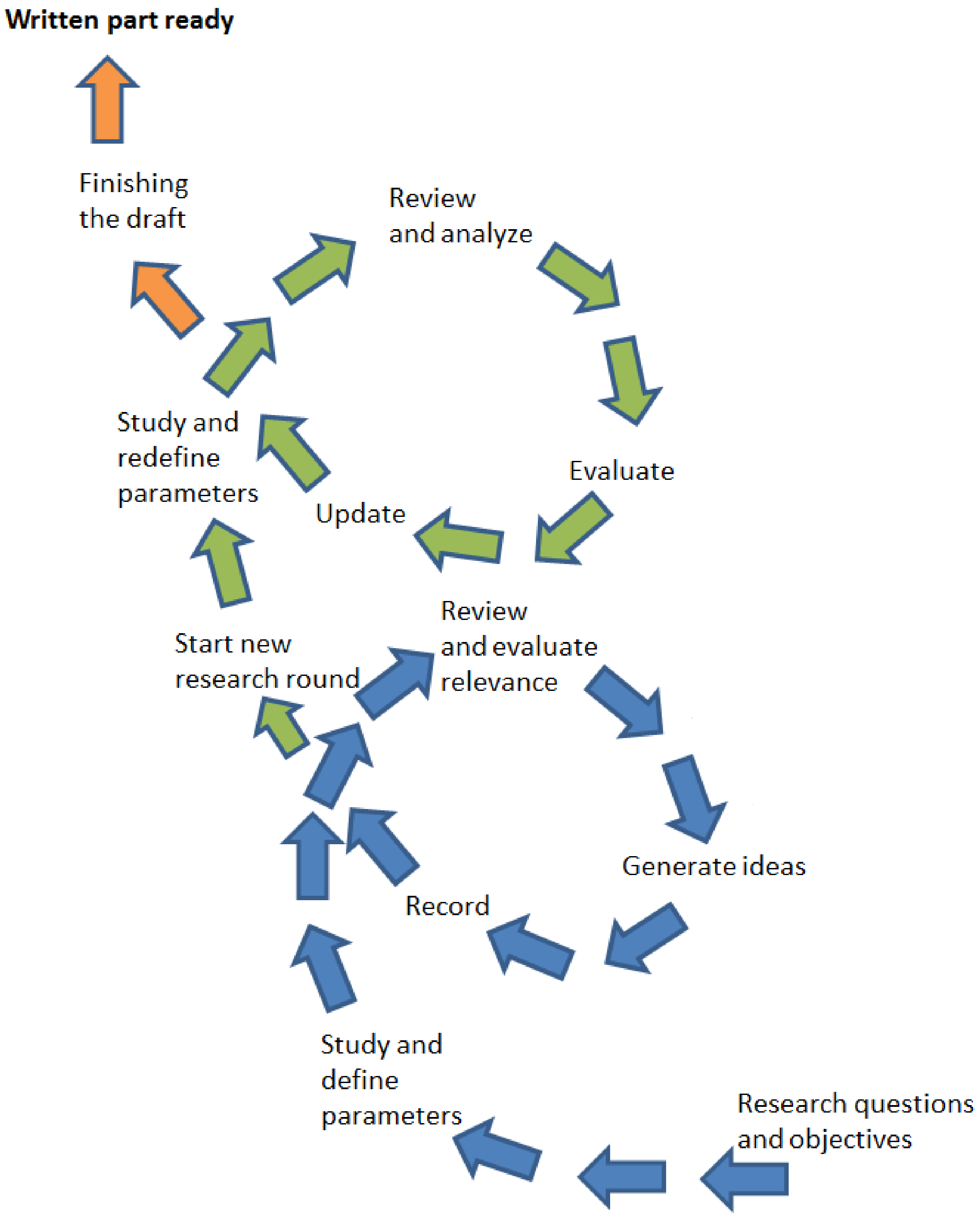

Figure 1.1 *The Study pattern* [4, p. 60].

As figure 1.1 shows, the literature part of the thesis is constantly under evaluation in order to find the most relevant information regarding to challenges of the thesis. The idea is to start the research by understanding questions and objectives. The next phase is to study literature and find necessary information for the thesis. During the evaluation phase the key point is to understand what was discovered and determine relevant findings. The last two phases involve documenting generated ideas and produced possible solutions. The second circle will conduct another research round, where several sections are similar to the first one. However, the information is now more conclusive after the first research round. Therefore, the second research round is concentrated on evaluation and updating of documented information.

1.3.1 Objectives

During this thesis, the case company's Sales and Operations Planning will be developed. All in all, learning the theoretical background of S&OP and Demand Planning is vital as well as getting familiarized with the case company's current Sales and Operations Planning policy. Overall, the development of the current S&OP processes is the most important.

One of the desired tasks is to find is the case company's data entangled with some other statistics. Thus, the research also includes global indexes and their correlations with the case company's sales data. This data is needed to form a conclusive demand plan, since statistical forecasting methods do not recognize information from outside the historical sales data. Despite the fact that finding the most suitable statistical forecasting method for the case company remains the priority target, there is a high interest to categorize products by their forecastability. In addition quality control needs to be built, in order to evaluate the output of the forecasting method. Finally, the research questions need to be answered during the thesis.

The main research targets are to:

- Categorize the historical sales data of the case company by its forecastability
- Find the most suitable statistical forecasting method for the case company
- Discover possible correlation between the case company and global business indexes
- Evaluate the forecasting method's output and suitability

1.4 Structure of the Thesis

This thesis consists of two main parts. The first part is a literature review containing a theoretical study concentrating on forecasting and Sales and Operations Planning. The literature review also explains how sales and operations planning, forecasting included, relates to supply chain management and quality.

The second part consists of the case company analysis focusing on empirical data and seeking possible solutions to challenges which the case company now faces. The results will be evaluated during this portion and discussed how the theoretical part relates and supports the research and the results. The part also explains the methodology and represents conclusions and recommendations for the future.

2 LITERATURE REVIEW

This chapter holds the literature review. It enlightens the need for forecasts, forecasting methods and benefits of forecasts. This chapter will introduce several methods and all of them are used during this research. All this is part of Sales and Operations Planning. S&OP uses forecasts to optimize inventory levels, production and purchasing. S&OP process gives guiding signals how to run Supply Chain Management (SCM). SCM, however, consists of several different stakeholders. These stakeholders will execute company's strategy and decisions made by S&OP process. Aforementioned stakeholders' performance is measured by different scales and techniques. More generally, a company's value can be evaluated by following return on investment (ROI) percentage. However, SCM, S&OP and forecasting have their own quality measurement techniques, which will, eventually, have an impact on ROI.

Figure 2.1 *Structure of literature review.*

This chapter is structured as figure 2.1 illustrates. Firstly, the literature review will introduce Supply Chain Management, secondly Sales and Operations Planning, thirdly under Sales and Operations planning, forecasting and techniques which are related to forecasting and lastly Quality and how S&OP is an enabler of good quality.

2.1 Supply Chain Management

Supply chain management refers to supply and delivery development and management, where products are manufactured and delivered to a customer [5, p 465]. Supply chain management also recognizes customer satisfaction as a part of supply chain; therefore customer's value in SCM plays a significant role. The stakeholders of the supply chain provide services to a customer keeping the costs as low as possible [5, pp. 465-466]. These customers can also be inside the company. Christopher (2013) states that supply chain is a network of suppliers and customers, which are linked to a company, which provides services or products [6].

In an ordinary supply chain, raw materials are received from suppliers. These materials go through a factory or a plant, which will use these materials to produce products. Thereupon, products are stored in warehouses and then delivered to customers [7, p. 1]. Supply Chain Management, however, is strategic coordination process, which consists of several stakeholders for the purpose of integrating supply and demand [8, pp. 503-504]. These stakeholders are suppliers, inventory control and logistics. Aforementioned stakeholders are meant to work together in a synchronized supply chain. However, all of these stakeholders are required to work cost-effectively throughout the entire system [9].

Supply chain can be divided to three different levels:

- Strategic level
- Tactical level
- Operational level

The strategic level involves making long lasting, high impact decisions in a company. These decisions, for instance, can be supplier selection or product design [7, p. 12]. The tactical level includes decisions regarding inventory policies and transportation strategies. Lastly, the operation level is comprised of decisions regarding daily operations such as scheduling [7, p. 12]. Each level has its own responsibility. However, all of them are driven by the same interest – to make profit. The strategic level makes the most influential decisions which often involve a lot of capital. Therefore, decisions are usually slow and carefully conducted. The tactical level, in comparison, makes decisions faster. The tactical level usually refers to middle level planning ranging from three months to one year. Since the decisions regard the future, the need for forecasting steps in. Forecasting can be used as a tool for decision making; however, there is lot of uncertainty involved when using forecasts. Nevertheless, the idea is to improve customer service and utilize assets even better. This all leads to a higher ROI.

Since, supply chains are increasingly becoming or are global; companies are searching opportunities beyond domestic borders [2, pp. 507-508]. The reason for this is assumed to be lower costs of production. The idea is to keep the company's operations cost-effective. Additionally, several global suppliers provide materials for manufacturing with a cheaper price. Nevertheless, companies which use global supply chain faces some challenges which domestic supply chain do not have. For instance, language barriers, cultural differences and increased transportation costs and lead times. Moreover, inventory control and coordination is lacking due to a too big operation environment. Thus, these companies need to anticipate aforementioned challenges. [9]

2.1.1 Different operating systems

A supply chain is built on a certain operation system. According to Koho (2012) there are four different operating systems and all of them have different ways of manufacturing products [10].

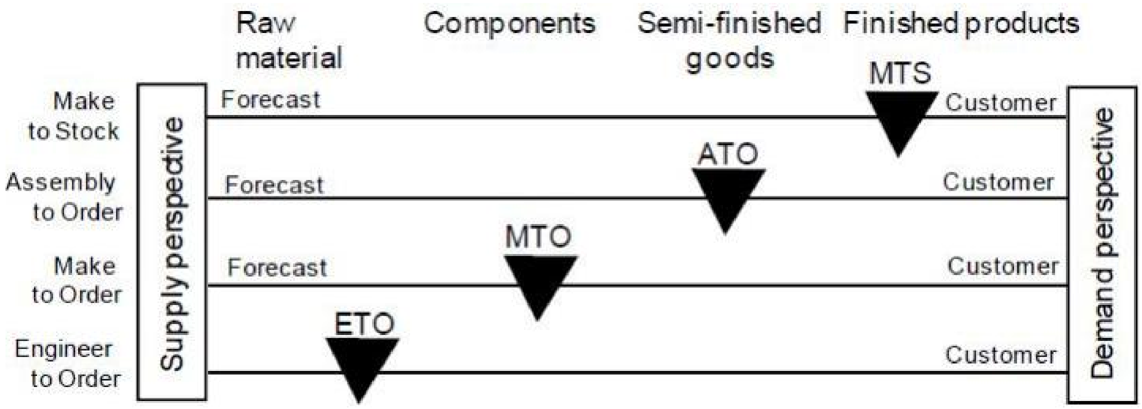

Figure 2.2 *Different operation systems* [10].

Figure 2.2 illustrates how quickly a customer can get the ordered product if delivery time is fixed for all operation systems. The figure reveals that the Engineer to Order (ETO) manufacturing process cycle takes a long time compared to Make to Stock (MTS). The products, which the ETO process manufactures, are custom made products. Thus, each product is individual and unique. From S&OP perspective, this manufacturing system is hard to forecast, since companies do not know the volumes or mix, which makes anticipation hard. According to Pohjalainen (2013), the challenges which the Engineer to Order approach faces, include the search of suppliers who can match the demand. Since delivery times play a key role in this system. Companies expect suppliers to a small safety stock to match the demand. Pohjalainen (2013) adds that one of the problems is that several suppliers are not willing to have a safety stock for the company, which makes selection of suppliers more difficult. Moreover, ETO products are hard to forecast. Make to Order (MTO) and Assembly to Order (ATO) make components or semi-finished goods to stock. The idea is to speed-up the delivery process and to improve customer service. Furthermore, most of these MTO and ATO products have similar components that can be manufactured to stock beforehand. S&OP makes this possible, since it recognizes the future demand and guides SCM to react on future phenomena by having a safety stock for finished goods or components. MTO products are typically components which can be easily utilized to make products. An ATO product, for example, is a product which has all necessary components available waiting for assembly. Customers choose desired features, and then the assembly is done quickly and delivered to the customer. A good example of ETO product is a unique product. Most of the components of the product need to be engineered before starting manufacturing. The MTS process enables quick delivery times to customers, since the products are not custom made. Usually these products are sold at a high volume or constantly; therefore it is possible to store products to stock and manufacture these products beforehand. [11, 12, pp. 24-45]

2.1.2 Quality as a factor of business

According to Haatainen (2013), one of the key factors of business is to satisfy customer's need by delivering the products on time. Juran (1986) states that quality is fulfilling a customer's requests [13, p. 3]. A delivery schedule is one of the most common requests. Regardless of the fact that quality is most often seen as a part of products function or sustainability, quality is a combination of customers' desires and needs [14, pp. 8-9]. In order to meet customers' needs, the delivery process needs to be constructed. Although, several companies already have these delivery processes, where material is manufactured to products and delivered to customer, the process does not work efficiently. Most often products are made too much or too few, resulting to waste of money. The problem, according to Juran (1974), is lack of communication and language problem. Top management talk about money, workers talks about regular manufacturing problems and midlevel managers needs to solve both of the problems by using both languages [15]. This challenge cannot be solved completely; however there is a way to ease the daily operations by balancing supply and demand.

Lean philosophy is known to reduce waste. These wastes can be recognized from S&OP point of view as demand variability, manufacturing variability and supplier variability [16, pp. 9-10]. Demand variability refers to customer demand. Commonly customers order different products with significant variability thus intuitive predictions are difficult. Therefore it is vital to categorize these products by their similarity, monetary importance and volatility. This kind of categorization enables demand planning to select what to forecast and which products could be exclude out of the forecasting process. Additionally these three aforementioned variabilities share a same challenge – lead time. Lean management attempts to reduce, among others, lead time by creating standardized working procedures. By reducing aforementioned variability, inventories will decrease as well as inventory costs. In order to create all this, the need of knowing the future is crucial. Therefore forecasting is important.

Many companies use different production approaches. These approaches are aforementioned ETO, MTO, ATO and MTS. From flexibility perspective MTS uses inventories to balance the demand. The flexibility of other approaches differs from MTS. Most often ordered goods are either too much or too few. Especially, if there is no collaboration between a factory and sales or operation management. This leads to over or under production. Although, collaboration and forecasting is brought to the process, there is still variation in the stocks. The reason for this is that forecasts are never right. However, the improvements are huge compared to situations where there is no forecasting or collaboration. [17, p. 28]

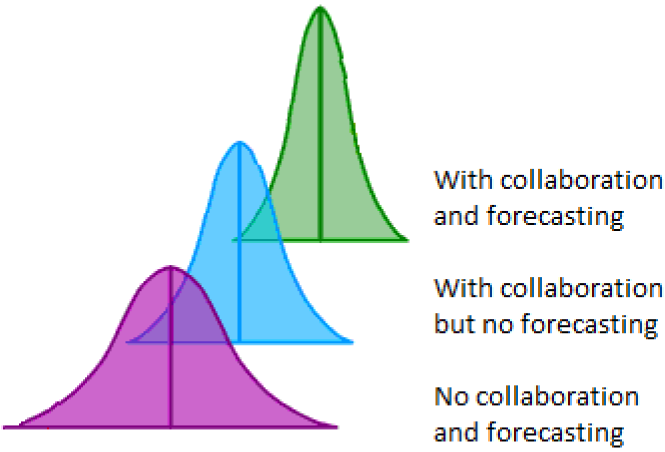

Figure 2.3 *Three different scenarios of collaboration* [18].

Figure 2.3 illustrates that, if sales management communicates constantly to manufacturing plants, the variation of over and under production decreases. Communication without forecasts is management's intuitions of the demand, which is not fact-based forecasting. Obviously, bringing forecasts also into the equation the variation will decrease even more [19]. The decreases results into an improved forecasting accuracy. This is a good measure to make business more profitable. [18, p. 13]

2.2 Sales and Operations Planning

Sales and Operations Planning have its roots to 1980s. At that time Oliver Wight discovered S&OP, but it got more popular after 1990s. The idea is simple, business is reviewed constantly and production is to be adjusted the right level to match the market demand [20, pp. 1-3]. In other words, S&OP is a link between business planning and detailed planning, scheduling and execution. In practice it means balancing demand and supply. If done right, S&OP can bring direct value to the whole company by reducing lead times and optimizing production. Most often companies work in a demand-driven business world. Therefore, strategic plans and business plans are made to cover demand. This demand is covered by making products and services to customers. The challenge of this model is communication. A business or strategic plan involves money but makes no plans for scheduling or production. The purpose is to connect strategic and tactical level together. This is where S&OP is required. [19, p. 11]

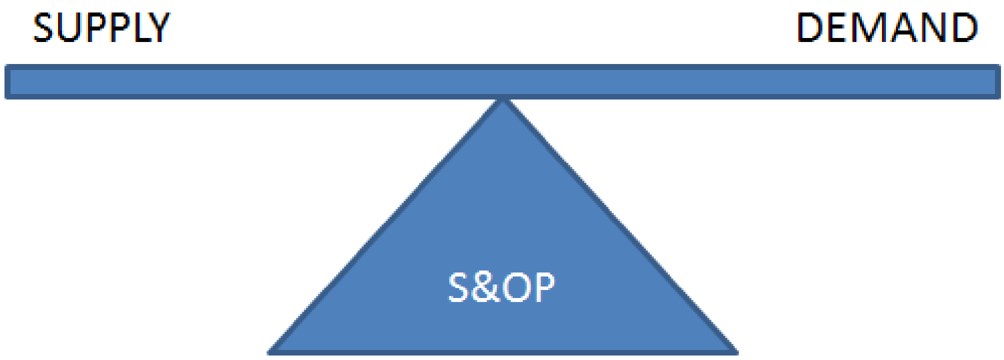

Figure 2.4 *S&OP balances supply and demand.*

If S&OP is working correctly in a company, as figure 2.4 illustrates, supply and demand is in balance and the company is reducing costs and lead times. This leads directly to customer satisfaction where ordered products are delivered on time. According to Feng (2011), Sales and Operations Planning is a widely known supply chain management process and the process has had lots of successful results in the companies which are using S&OP processes [21]. Sales and Operations Planning is often recognized as a tool for long term planning. It tries to provide right action plans for companies using the company's business strategy as a guide line [22, p. 514].

2.2.1 S&OP process

According to Wallace (2008), Sales and Operations Planning is a constant process. The goal is to improve and optimize production and capacity by matching the demand. Sales and Operations Planning is also referred to as a communication tool of managers. In practice it is a link between top level managers and production units focusing on keeping demand and supply in balance. [19, p. 9]

Figure 2.5 *Sales and Operations Planning Process circle* [23].

As figure 2.5 points out the process is running constantly. Usually the S&OP process is a monthly process. This means that figure 2.5 describes a monthly cycle. There are four major topics which form the S&OP process: [19]

1. Demand planning
2. Operations planning
3. Pre- S&OP meeting
4. Executive S&OP meeting

The demand plan process is based on historical sales data. The demand plan can be local or global depending on what kind of business the company conducts. The demand planning process starts as follows: a group of sales and marketing managers will review their demand plans and distribute them to a global S&OP sales manager. According to Wallace and Stahl (2006) there should also be a phase before the demand plan. This phase is noted as data gathering [24, p. 39]. Nevertheless, demand planning is based on knowledge which comes from company's sales and marketing teams. The demand plan phase will recognize several different aspects which can influence the future. For instance these aspects are: new product launches, competitors, price changes, big orders, economic conditions, seasonality or industry dynamics [24, p. 41]. Huttunen (2013) notes that the demand planning phase is useful for recognizing products which are becoming old in the markets. In other words those products which are near the end of their life cycle.

After the demand planning phase follows the operations planning phase. During operations planning, operations managers will create a plan to match the demand plan during current S&OP month. The operations plan tries to cover all of the S&OP time frame from 12 to 24 months [25]. Occasionally, if nothing or little has changed in the last periods or the demand plans do not have remarkable variation, there will most likely be no reason to alter the operations plan. However, if there are big changes in the demand forecast or a need to reduce over or under supply then the operations plan has to take action [26, p, 8]. A good example is to ramp down old products' production.

The third phase is called Pre- S&OP meeting. This phase will hold the preliminary meeting before the actual executive S&OP meeting. The phase will review all which will be showed to executive managers. The idea is to form an agenda for the meeting and cover all bases so that no surprises can be found. For this meeting, some suggestions regarding challenges of balancing the supply and demand were made beforehand. The purpose of the Pre- S&OP meeting is also to generate recommendations for the future plan. There is also a key interest to form scenarios showing alternative courses of actions to solve given challenges. [24, p. 45]

The executive S&OP meeting is the last phase of the S&OP process. This phase is the decision phase where all decisions are made to optimize productivity. According to Wallace and Stahl (2008) the general agenda is to review customer service performance, check business plans, make decisions and check production rates [19, p. 63].

2.2.1.1 Characteristics of S&OP

As chapter 2.2.1 explains, S&OP is a monthly process which is divided into four or five phases. All phases rely on their respective preceding phases. Therefore, the S&OP process is a discipline process, where delays are not welcomed. The reason why S&OP process is commonly a monthly process is that the demand fluctuates and company's production tries to match it by utilizing the information which S&OP provides. Aforementioned phases try to balance demand and supply [27].

One of the most important targets for SCM optimization is stock or inventory control. The S&OP process can be most effective when it has direct impact on stocks. In other words, a successful S&OP process reduces lead time to customers by adjusting inventory levels into right levels. In practice it can reveal the right number of products which is needed to cover the demand [28, p. 560]. Aforementioned optimizations can be achieved by using S&OP. However, customer demand is always fluctuating. Therefore inventory levels needs to be optimized in a monthly basis in order to match the demand. It is obvious that a huge stock can always meet the demand. The downside, however, is that the inventory costs will increase if stocks are big, without mentioning that manufacturing plants are on over production trying to match the company's service level by feeding finished goods into stocks [29, pp. 606-609]. For else manufacturing approaches, such as ATO, MTO and ETO, the S&OP process tries to match with the demand by anticipating what will happen it the future by purchasing components and material beforehand [19].

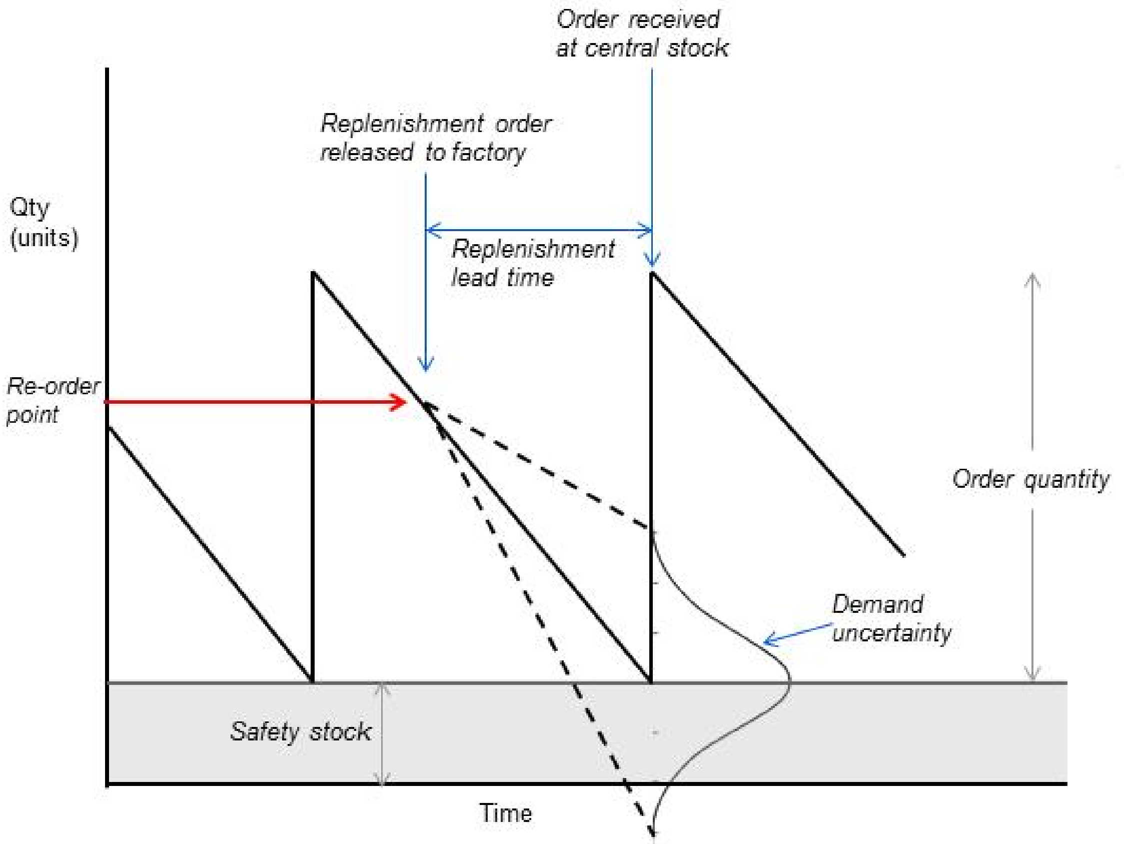

Figure 2.6 *S&OP as a tool for inventory control* [30].

As figure 2.6 illustrates Sales and Operations Planning have an ability to adjust inventories into right levels. This means that stocks have enough products to match the market demand. In other words safety stocks and reorder points are in the right levels.

One task, however, has huge impact on the S&OP process - forecasting. Forecasts are the backbone of the whole S&OP process. Regardless of the fact that forecasting is an enabler for effective S&OP process, forecast error needs to be calculated in order to know the uncertainty of the forecasts. Therefore when using forecasts, one needs to recognize how significant the errors and the uncertainties when making plans into the future.

2.2.1.2 SWOT Analysis of S&OP

According to Wallace (2008), Sales and Operations Planning is recognized as a top management tool [19, 24, 31]. Therefore, S&OP has a lot of good aspects which support company's business plan. Most often, a strategy has been made on how to conduct business. This strategy is a guide line for different stakeholders. Sometimes, however, the plan does not work. Demand is not matching with supply. Therefore S&OP is needed to from a bridge between demand and supply.

Strengths:
There are several good aspects about S&OP. For instance, it gives information on how to set inventory levels, coordinate and optimize production. But above all guidance on how to balance demand and supply. With this process, top managers can make decisions faster and easier [32].

Since the S&OP process evaluates how the future behaves by calculating values of the historical sales; it is easy to recognize if a product is losing customers' interests in the markets. In other words, the process can be used for recognizing when products are at the end of their life cycle. Thus, top managers are able to make decisions regarding to the product's production [33].

From the business point of view, Sales and Operations Planning improves customer service. Basically, it enables a company to deliver products on time. S&OP stabilizes supply rates, which will lead to higher productivity for all stakeholders; manufacture plants, suppliers and contract manufactures. Sales and Operations Planning also enables companies to make changes to supply since it provides information from 12 to 24 months into the future. [24, pp. 3-4]

Weaknesses:
According to McNeil (2006) some companies often find S&OP process too long and too infrequent [34]. Although the process uses a monthly cycle, in many business industries changes happen even faster. One of the weaknesses is that S&OP relies heavily on technology. Therefore if required technology, for instance computers and calculation software, is not available the process is unable to work. Additionally, S&OP uses a tremendous amount of data which is impossible to control without computers, since for instance, a lot of forecast calculation is needed to predict the demand [34]. Another weakness is that Sales and Operations Planning is recognized as a project. Therefore, S&OP does not have constant support from the Chief Executive Officer (CEO) or the S&OP sponsor [34]. The result of this is that S&OP loses its value and it will not aid sales, operations or any stakeholder. Lastly, one of the basic assumptions is that S&OP is easy and the whole sales staff knows how to run the process. [19, p. 175]

Opportunities:
S&OP is a good tool to aid top management to make decisions for the business. This will result to cost reduction and better ROI if the process is done right. However, it is commonly known as an aggregate planning tool. Therefore, it has its limitations. For instance, too detailed planning is not wise to conduct. That gives S&OP a clear operation environment - aggregate level planning. This limitation is clearly gives an oppor-

tunity to expand if necessary, when S&OP process is mature enough. Although there is a clear operation environment, detailed planning would be a great asset. However, S&OP is recognized to be an aggregate planning tool. Despite of the fact that it is possible, it involves a lot of effort and time [31, p.52]. Therefore, S&OP works best in the aggregate planning level. If S&OP is done right, it will increase service levels and attract more customers [2, pp. 600-625].

With the aid of computers Sales and Operations planning gets faster. Many authors recognize that the regular S&OP process pace is one month. However, it could get shorter if technology evolves. Although a possibility exists of a faster pace, the need to conduct faster S&OP is not common [24].

Threats:
Firstly, one of the most common threats is ownership. Stakeholders need to clarify their responsibilities from the beginning of the S&OP process [35]. Secondly, since the S&OP process relies on technology and several computer-aided forecasting simulations there are risks that users forgot what S&OP is about. As a result it could derail the S&OP process from following the company's strategy. Finally, the S&OP process is a highly disciplined process. The preceding chapter concludes that the S&OP phases need to be executed in order. Therefore if some phase is delayed the whole process is late. Additionally, S&OP process involves a lot of data. If the data is inaccurate or not available the process will collapse. [19, pp. 175-180]

2.2.1.3 Benefits of S&OP process

Sales and Operations Planning can provide huge amounts of savings. Moreover, it can bring more customers for the company. This is a result of a good service level, which indicates that ordered products are delivered on time. However, a 100% service level cannot be reached unless investing a significant amount of money to inventories.

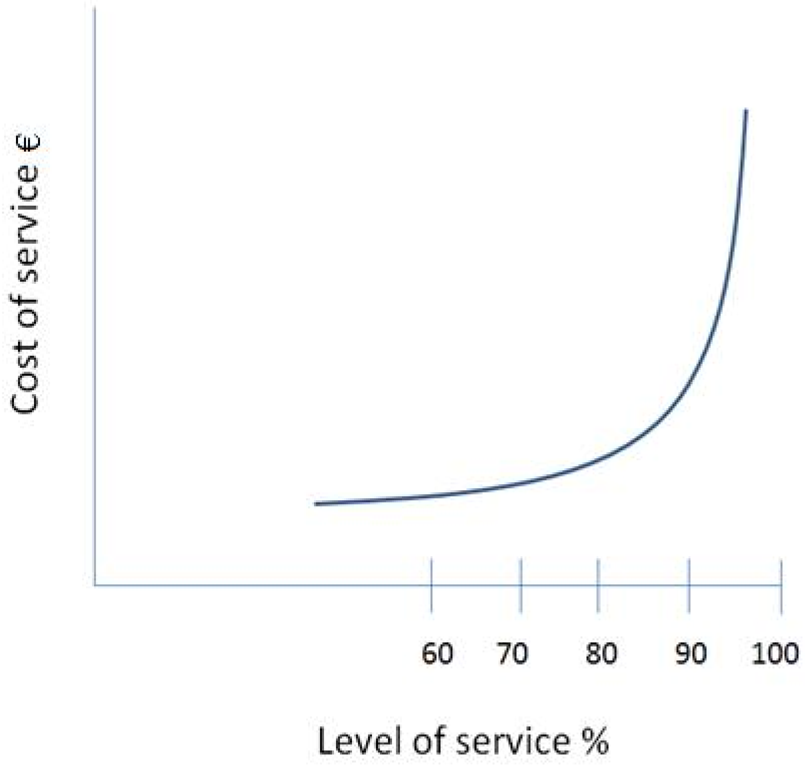

Figure 2.7 *The costs of better service level* [23].

In this figure 2.7 it is easy to observe that if the service level is wanted to be kept above 90 percent it will require a big investment. In practice a 100 percent service level would require huge inventory as well as high production level. However, the positive side of keeping a good service level is that customers tend to become regular customers, when the ordered products can be delivered on time [32]. Haatainen (2013) states that S&OP is a management tool to optimize production, inventories and coordination. It has direct impact on company's business and on ROI.

2.2.2 Summary of S&OP

Dougherty and Gray (2006) state that S&OP is one of the most important business processes of the last two decades [36, p. xvii]. Many companies use S&OP as a top management tool to improve their business. Sales and Operations Planning is used to: [19]

- Adjust inventory levels
- Optimize production
- Balance demand and supply

Using S&OP correctly and constantly, good results will appear. For instance shorter lead time, better service level, more customers, more permanent customers and above all higher return on investment percentage, since less money is invested. The reason for this is that high level managers are able to make decisions which will support several operations. For instance, S&OP provides information which enables adjusting production into right levels, reducing over and under production. [37, pp. 47-71]

S&OP process consists of four main phases. The process commonly uses a one month cycle. During the process a company's sales data is used to form a reliable demand plan for the future and that demand plan is a target for operations which will create a game plan how to reach aforementioned target. At the end of the process, top level managers make decisions to adjust inventory levels and production into right level to maximize service level investing as little capital as possible.

2.3 Forecasting as a part of S&OP

Forecasts are decision making tools which provide information on what a company should do next [2, p. 66]. Forecasts have an extremely high role when a company makes minor or major changes. High level managers want to make right decisions and forecasting is the tool for that [19, p. 19]. Forecasting also gives several advantages given by the information of the forecast. It enables managers to do scheduling, acquire resources and determine resource requirements [3, p. 5]. An important task of forecasting is to give decision makers and policy makers a good understating of the uncertainties of the future [38, p. 7]. Sales and Operations Planning uses forecasting as a tool. The reason for this is that top level managers want to make right decisions to optimize inventories and production based on fact-based information which the forecasts will offer. Forecasting also provides information which enables suppliers to meet the company's needs. In other words, the information that forecasting provides is transparent throughout the value chain.

Next subchapters will introduce some techniques on how to forecast in the S&OP framework. There are two clear approaches to forecasting. The first one is a quantitative method which is based on solid data. This kind of method needs numerical information in order to make a forecast. The second method is called a qualitative method. The qualitative method relies on people's feelings, intuitions and ideas. The qualitative method is used if statistical data is not available. If sufficient data is not available or qualitative information is insufficient, one cannot predict anything. The table 2.1 clarifies the stage of forecasting and when to use the two different approaches. [3, p. 8]

Table 2.1 *Foresting methods categorized by their application* [8].

Quantitative:	Sufficient quantitative information is available.
Qualitative:	Little or no quantitative information is available, but sufficient qualitative knowledge exists.
Unpredictable:	Little or no information is available.

Both the qualitative and the quantitative method have several techniques to forecast. Regardless of the fact that both methods try to form a forecast or a prediction, the objectivity of these methods differ from each other. The qualitative method is more predictive than forecasting, because it relies on human opinions or intuitions [8, p. 69]. Therefore the qualitative method has human bias. It was mentioned earlier that the quantitative method relies on solid statistical data. However, sophisticated quantitative forecasting methods also rely on human judgment, since quantitative forecast only involves statistical values from the past [39, p. 26].

2.3.1 Forecasting ranges

There are three ways to categorize forecasts by their forecast range. Some companies use all of them, some only one or two. Every single one of them works best by the way it was designed to. The aforementioned forecast ranges are [40, p. 106]:

- Short-range forecast
- Medium-range forecast
- Long-range forecast

Each one of them is used for specific forecasts. For instance, short-range forecast is used, as the name indicates, for forecasting short periods of time. The range usually is from three months to one year [38, p. 9]. Short period forecasts are used for, i.e., purchase planning, job scheduling, levels of productions and levels of workforce [40, p. 106]. Medium-range forecast's range of time is more unclear. Some authors such as Heizer & Render (2006) and Makridakis & Wheelwright (1998) argue that the range begins from three months or one year, but they still recognize that the range could stretch into two years. This medium-range forecast can be used for S&OP and budgeting [38, 40]. Medium-range forecasts, as well as long-range forecasts, use more quantitative methods and mathematical forecasting than qualitative methods [40, p.106]. Nevertheless, medium-range forecasts do not require as much details as short-range forecasts [28, p. 498]. Long-range forecasts are used for, i.e., planning new products and facility locations. The range of Long-range forecasts covers the time frame from two years and above.

2.3.2 Overview of Quantitative methods

The quantitative method is a mathematical method. Data which work as an input for the qualitative methods is based on historical and forecasting data of a company's products. It uses time series models and associative models [40, p. 109]. Makridakis & Wheelwright (1998) point out three important steps that need to be recognized before quantitative techniques can be used. These steps consist of the following [3, p. 9]:

- The information needs to be formed of numerical data
- Historical data is available
- Historical data has to be continuous and relevant

The qualitative method can be divided into two models. These models are the Time Series model and the Causal or Associative model. The Time Series analysis is an explicit tool to recognize trends and patters from the historical data. Weakness is that it strongly relies on the provided data [28, p. 497]. On the other hand, the Causal or Associative model includes other factors of forecasting. For instance, competitors pricing or advertising budget [40, p.109]. The next table will introduce a few quantitative models.

Table 2.2 *Five quantitative methods* [8].

Objectivity: Objective	
1. Naïve approach	Time series model
2. Trend projection	Time series model
3. Moving averages	Time series model
4. Exponential smoothing	Time series model
5. Linear regression	Causal/Associative model

As the table 2.2 shows the objectivity of quantitative methods is objective. All of these models rely on solid data. Therefore, the aforementioned three steps need to be valid in order to use these models. The following paragraphs will introduce more of these models.

Naïve method:

It is most commonly used in the business world. It is also the easiest and simplest forecast model. The naïve method uses current period's demand as a base for next period's forecast. Naïve method can be only utilized from stable patterns and short period forecasting; otherwise the forecast error will increase. The formula (2) is presented in appendix 1. [8, p. 70]

Moving averages:

The Moving averages technique is, overall, a simple forecasting technique. It uses the formula (4) to form an estimation of the future for the desired period of time. Comparing Moving averages and Naïve methods, the Naïve method only takes one period of time under investigation; whereas Moving averages observation scale can be several time periods [2, p. 72]. Chase points out that even though the Moving averages method is more conclusive than Naïve method, the Moving averages formula, in appendix 1, is easy to generate and it is easy to use. [41]

Regardless of the easy usage and conclusiveness, it also has some disadvantages: [41, p. 112-113]

- Data requires more storage space. Calculated average alone is not enough if there is a need to recheck the data or form a bigger average
- Although the Moving averages method creates a good mean, it does not handle trends or seasonality well
- Forecasting error increases toward the future, since the forecast will eventually be a flat line and will not mimic the historical sales data

Exponential smoothing:

The exponential smoothing method is more advanced than the previous three, since it has a smoothing factor. It forms similar forecasts with some exceptions. Overall this method is easy to use. The exponential smoothing method does not use tremendously amount of data to form a forecast. However, it forms a reliable forecast combining historical data and putting weight into past data of the time frame [42, p. 70]. The weight is added to the mathematical formula by using the exponential smoothing constant α. One who uses the formula decides how strong α should be. The value has to be between zero and one. Sometimes forecast errors can be reduced if α is higher. Usually this is needed if there are big changes or fluctuation in the historical data [28, p. 510].

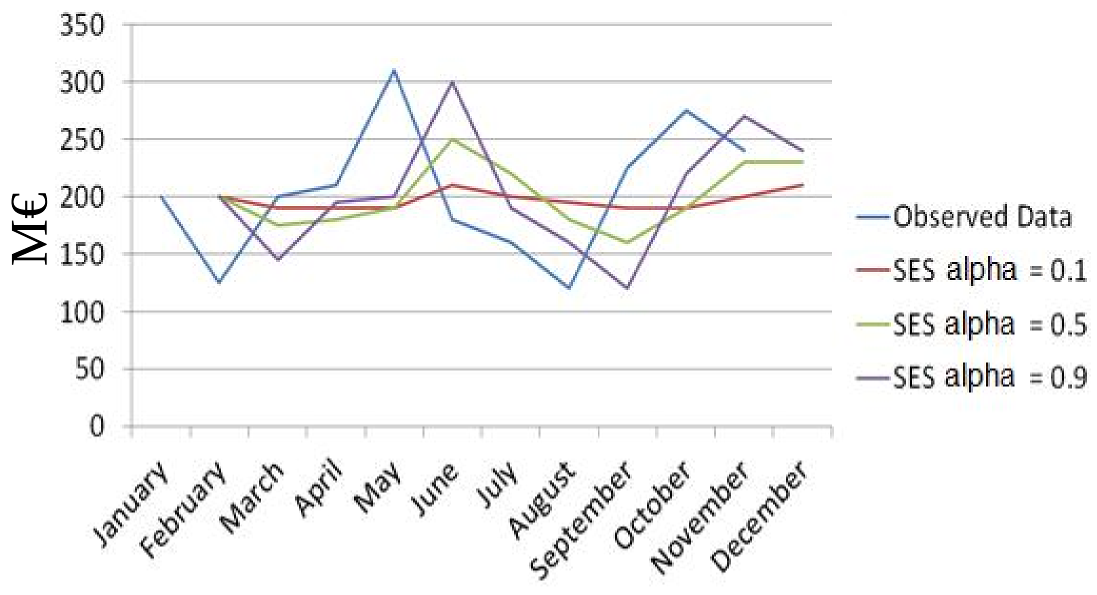

Figure 2.8 *Behavior of three different Single exponential smoothing methods* [3, p. 152].

Figure 2.8 points out, α plays a key role if there are big fluctuation in the data. The higher the value is, the stronger the Single Exponential Smoothing (SES) (5) data correlates with the actual data. If α will have a value of one, the forecast would be exactly the same as the previous forecast. That would be the same as Naïve forecasting method. On the other hand, alpha's value closing to zero the forecast would be the Moving averages method [41, p. 116]

Well-known exponential smoothing methods:
Single exponential smoothing method is the simplest. It uses a weight constant α, the current period's forecast and actual value. As the formula (5) in appendix 1 shows, the new forecast is just the forecast from the previous time period added by the forecast error. Regardless of the fact that the formula is simple, it plays a big role in forecasting. [3, p. 148]

Holt's two parameters method (6), also known as the Holt's linear method, has a more advanced approach to forecasting than the SES method. It also has a weighted coefficient α, but it also includes trends β [43, p. 624]. Holt's two parameters method is more complicated than the already introduced methods. This method requires two sub formulas and a master formula, which are shown in appendix 1[41, p. 120]. The master formula is not more complicated than the sub formulas. As simple as the master formula looks, Holt's two parameters method beats SES method in all aspects of errors. This is a result of value β, which takes trend into account, whereas SES does not recognize trends at all. However, Holt's two parameters method does not recognize seasonality. [41, p. 121]

The last exponential smoothing method is called Holt's-Winters' three parameter method (9). This method is the most advanced method of the methods which are introduced. It is similar to weighted exponential smoothing method, Holt's two parameters, but it has a third parameter γ to evaluate seasonality [3, p. 161]. As the Holt's-Winters' three parameter formula shows, it has three components which are: level, trend and seasonality of the time series. These components make a strong forecasting method. Comparing with the other methods so far introduced, Holt's-Winters' three parameter method has, overall, the best abilities to form a reliable forecast. Although, it is more complicated than the other introduced statistical forecasting methods. The formulas are presented in appendix 1.

Linear regression:
The linear regression application, a trend projection, is a medium and long-range forecast technique. It adjusts a trend line using historical data. This technique most often uses linear trends and it works best when variation is low. The trend projection formula

(3), in appendix 1, will show how to generate the slope of the regression line. [40, p. 120-121]

This linear regression is classified as a causal model. It forms a linear forecasting method from gained data. The causal model requires correlation or relation analysis. The idea is to find a connection between two different data sources and form a forecast according to that knowledge [44]. Afterwards, for instance, the data can be plot on a chart where linear regression will take place. Linear regression will fit a straight line through the data [3, p. 189].

The linear regression formula is a basic model of a regular linear line. Figure 2.5 will shows how the linear regression works in practice.

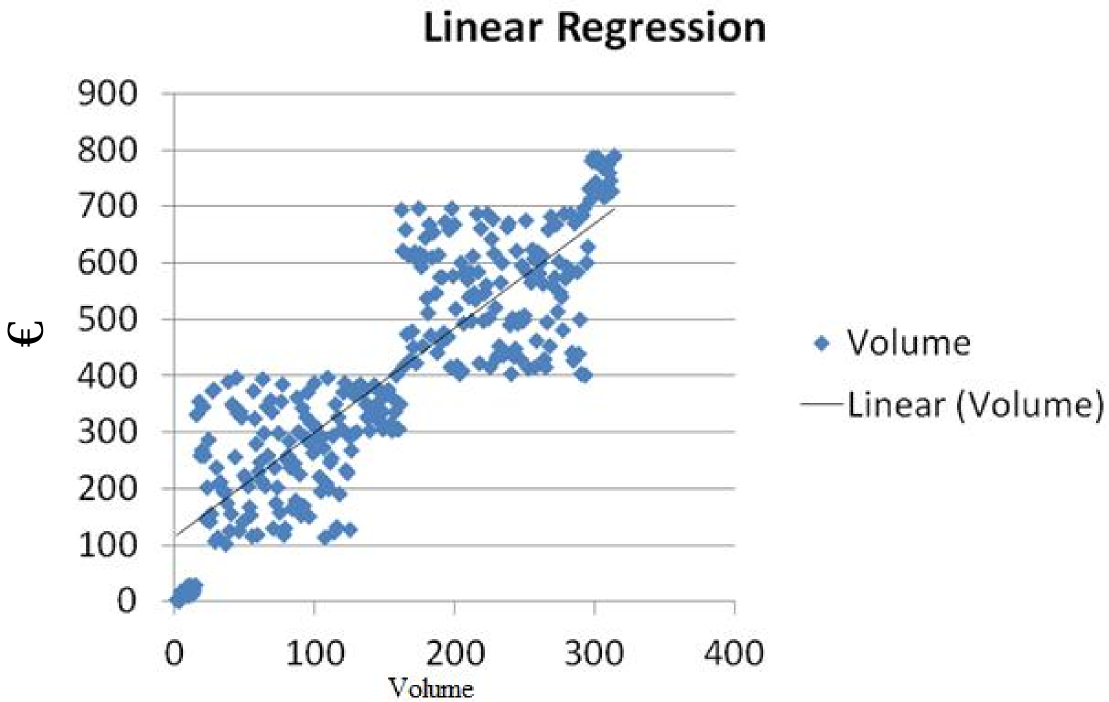

Figure 2.9 *Linear Regression line in practice* [41, p. 131].

As one can observe from figure 2.9, the regression line is plotted and fitted on the plotted data. Nevertheless, the linear regression is a useful tool to make decisions considering inventory management or process management [28, p. 506]. The formula is presented in appendix 1.

Brown's method:

Brown's method (13) is often referred to as just an exponential smoothing method. It is similar to Holt's two parameters method, but is not that advanced. The forecast formula uses a smoothing parameter which the user will input. Like the previous forecasts, the brown's method uses last period's seasonality, trend and demand values. The first values need to be estimations of what the data should be, since historical data is not always available [45]. As the Brown's formula shows, in appendix 1, it uses already calculated values of seasonality and trend.

Bayesian method:
This method is a combination of four different forecasting methods. It uses Moving averages, Adaptive exponential smoothing, Simple regression (SR) and Brown's method [46]. All of the methods are divided by four and then added together. Bayesian, in this thesis, is modified to use Moving averages, Holt's-Winters' as an adaptive exponential smoothing, Trend projection as a simple regression and Brown's method in this thesis. Although, the Bayesian forecast formula (18) is a simple one; it requires four different forecasting methods to work. Therefore, it is the most time consuming forecasting method to build, if it built without having any of the forecasting methods ready. The formula is presented in appendix 1.

2.3.2.1 Best fit

Many companies use forecasting software which uses several different quantitative forecasting techniques to calculate forecasts. This modern software tends to have an option for selecting the best forecasting model for specific data. This option is called a best fit option. This kind of software calculates first several forecasts and then calculates errors such as bias or means absolute deviation and mean absolute percentage error. After these operations the software evaluates which forecasting models is the best according to errors. The model which has the lowest error percentage, based on historical values, is chosen to be the best forecast. [47, 48]

2.3.3 Overview of Qualitative methods

Qualitative method is referred as non-statistical forecasting; therefore it cannot make exact fact-based forecasts, since the forecast are based on human intuitions. Nevertheless it is important input when creating demand plan, since human opinions plays a key role in the demand plan. As the table 2.1 shows that qualitative methods are used most commonly when historical data is not available or there is only some data available. Qualitative methods use human knowledge. In other words, it is collection of people's opinions or judgments. Although qualitative method, however, comparing to quantitative, have a lot of uncertainty, it is nevertheless, important when there are no other data available. This kind of situations appears when new projects or products are launched and similar examples from the past are some or none. That is one reason why qualitative method is used as medium or long-range situations [3, p. 12].

There are qualitative techniques which are used to help the decision makers make the right decisions:

- Jury of executive opinion
- Delphi method
- Sales force composite
- Consumer market survey

Delphi method is the most commonly used quantitative method in business world. It uses a survey which is used to collect information or opinions from problem related personnel. Personnel are divided to three different groups:

1. Decision makers
2. Staff personnel
3. Respondents

This kind of method gives each group several questions. Answers will be evaluated and summarized. Several question rounds appear until results are enough stable and conclusive. [4, p. 29, 49, p. 5]

According to Miles (1994) Qualitative data is human intuitions and assumptions, for instance, the Delphi method uses. It can recognize something else which qualitative data cannot, since it is based on human intuitions and opinions [50, p. 10]. There is also uncertainty within the qualitative data. Miles referred qualitative data as a real life data. Therefore there exist problems such as personal biases. [8, p. 71]

2.3.4 Summary of forecasting

According to Heizer and Render (2006), the best forecasting method will form by combining both qualitative and quantitative methods, however combined method should be measured by its forecast accuracy, usability, implementation costs and information [40, p. 108, 51]. Some companies, however, are not using both methods together. Reason for this is that it costs too much and other reason is that either qualitative or quantitative method is adequate enough. Regardless of the fact that forecasts are never right, they give company leaders and managers an idea or a vision what could happen. Forecasts also provide information of current path of business and where it will lead the company. However, the forecasts are still projections of the past and will not fully define the future as before mentioned. Simchi-Levi states (2007) that there are three basic rules about forecasts [7, p. 57]:

1. In every case the forecasts are always wrong
2. The forecast get more and more worse the longer the forecast horizon is
3. Collective forecasts have the best accuracy

These rules need to keep in mind when utilizing forecasts. Therefore it is important to understand how the uncertainty varies when making plans into future.

All in all, forecasts are power tool to aid business to grow and maintain high operation level. Some companies, however, are not fully able utilize forecasts to their business, since, customers tend to order customized products which will result high lead time, especially ETO production approach.

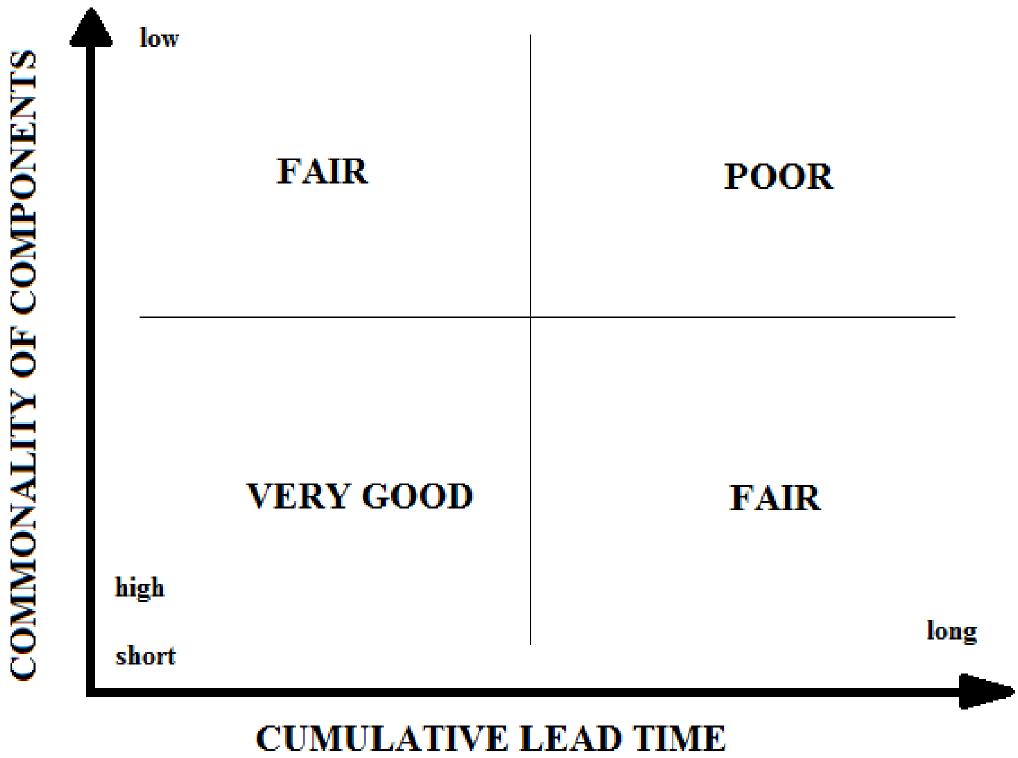

Figure 2.10 *Opportunities to forecast at higher product hierarchy levels* [31, p. 53].

Figure 2.10 illustrates that forecasting gets harder when lead time increases and components or products gets more customized. Therefore, the accuracy increases, if lead time is short and components are similar. Conclusion of figure 2.10 is that, commonality is an important attribute when conduction forecasts. Secondly, when lead time increases one needs to forecast far into future accuracy tend to decrease. Therefore, manufacturing approaches such as ETO, MTO and ATO need to have long or mid-term forecasts to match the demand, since usually lead time is relatively long.

2.3.5 Ways to measure errors in S&OP's forecasts

One of the most important Key Performance Indicators (KPI) of Sales and Operations Planning is forecast's accuracy measurement. This accuracy can be measured by different mathematical formulas. Commonly, for instance, mean forecast error (MFE) (23), mean absolute percentage error (MAPE) (22), mean absolute deviation (MAD) (20) also referred as variability and bias is used. Aforementioned error measuring techniques' formulas are presented in appendix 2. These error measuring formulas monitors the actual forecasting, but they also provides an opportunity to improve forecasts [52, p. 122]. Despite the fact that forecasts can be improved, the key question to S&OP forecasts is: how accurate should the forecast be [31, p. 33]? Obviously, companies desire to have the best possible forecast accuracy. However high forecast accuracy requires massive amount of time and effort. Therefore companies need to decide the accuracy levels in order to avoid wasting resursses.

Heizer and Render (2006) introduces a tracking signal method for forecasts. The idea of the tracking signal is to monitor how well the forecast predicts actual values [40, p. 133]. This method uses two different formulas MAD (20) and running sum of the forecast errors (RSFE) (21). The formulas are presented in appendix 2.

The tracking signal formula (19), in appendix 2, provides information how the forecast behaves. Obviously, forecasts are not accurate and there is always variation. Therefore companies need to set control limits when to reanalyze the historical sales data's behavior or to change the forecasting method. Nevertheless, upper and lower control limits informs when a company should take actions to correct forecasts. There is not right answer how to define the upper and lower limits. Despite, these limits are not recommended to set too tight. Otherwise, forecast is looked or overlooked too often. [2, pp. 90-95]

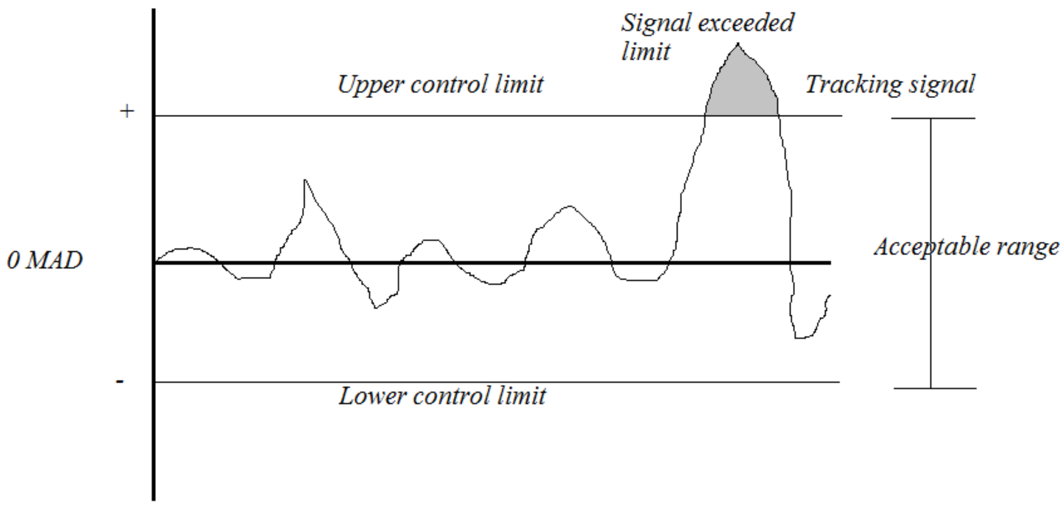

Figure 2.11 *Tracking signal* [2, p. 91].

Figure 2.11 illustrates that the forecast values deviation can be easily to monitor, if limits are set into right level. Since, the tracking signal is not the only way of measuring error; companies tend to use different approaches to control forecasts and also to monitor errors. MAD and MAPE are good methods to calculate forecast errors. However, for the production and the inventory planning MAPE measuring is possibly the best, since inventories tend to balance in time if errors are equally positive and negative. [31, pp. 38-40, 40, p. 133, 52, p. 122]

2.4 Quality in a value chain

There are several different value indicators. For instance, production can be measured by finding defects, delivery quality can be measured by measuring on time deliveries and forecast accuracy can be measured by using error formulas. Since, the focus of this thesis is S&OP and forecast process, the key focus will be on statistical forecasting error measuring.

According to Goetsch and Davis (2010) the most important factor of business is to measure customer satisfaction. Customer satisfaction is measured by using feedback. Usually companies use their own web pages to collect feedback. Sometimes, feedback is given directly from customer to seller. In many cases, customer satisfaction is related to product's quality and service [37, pp. 142-147]. Seybold (2001) suggest that companies should take measuring even further by adding to customers value measures such as changes of permanent customers, defections and acquisition costs [53]. Despite the fact that these are good additional perspectives, companies adhere to measure service level, customer satisfaction and supply chain performance measures [7, pp. 380-381].

Commonly, error measuring is acknowledged to be a quality tool for production. When using this tool, quality can be measured, however, it also provides information, which aids managers to improve company's processes [53, p. 122]. This leads to better product quality when defects are detected less. Regardless of the fact that error measuring is seen as a tool for production, it can be used for optimizing inventories and production. A good example is S&OP, which uses forecasts as an enabler to balance demand and supply. Although, forecasts clearly aid factories to optimize production, forecasts can be also optimized further by using different ways to measure errors.

According to Wallace, forecast quality can be improved by selecting forecasting data. This indicates that data analysis is necessary to complete before forecasting is conducted. During this analysis a key interest is to find variability. If the data varies highly, it most commonly cannot be forecasted. This approach is considered to be Lean style approach to forecast where waste is eliminated from the process. Another approach is to accommodate the variation. This typically refers to accepting the variation and to use this as an advantage. [16, pp. 9-10, 54]

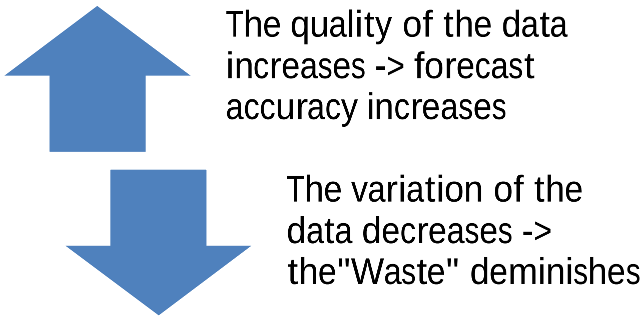

Figure 2.12 *Results of selecting the forecast data.*

Figure 2.12 illustrates the results which the selection of forecast data generates. This weighs even more the importance of data analysis.

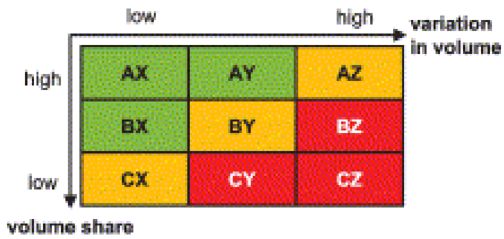

Figure 2.13 *The categorization of the ABC/XYZ analysis* [55].

In order to minimize the waste of the data an ABC/XYZ analysis is good to conduct. This analysis separates products into nine different categories by their variability and monetary importance. ABC classification is for monetary importance and it is defined as follows: A products cover 75 percent, B products 20 percent and C products 5 percent of the monetary importance. The XYZ classification, however, goes as follows: X products' variability is between 0 and 75 percent, Y products' between 75 and 133 percent and Z products are greater than 133 percentages. With this classification the ABC/XYZ analysis will evaluate each product resulting to categorization, which will inform which products can be forecasted and which needs to leave out of the forecasting scope. [55, 56, 57, 58]

Occasionally the chosen forecasting method is not effective and the forecast accuracy is not the best possible. Kolassa (2009) introduces a forecast value adding line which evaluates the current forecasting method by its suitability for the current data. The forecast value adding line informs the company when there need to conduct action by changing the current forecast.

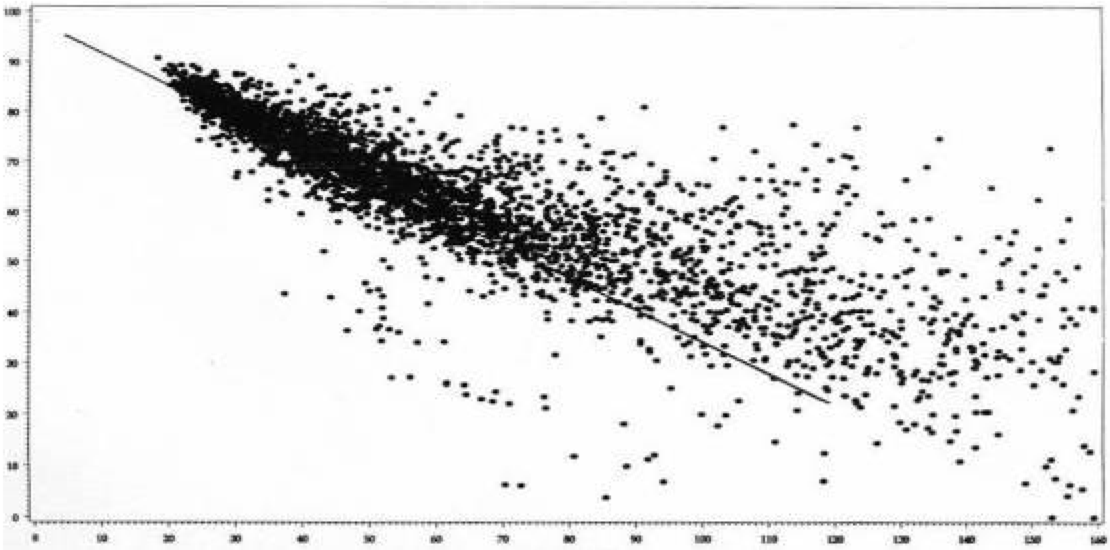

Figure 2.14 *Forecast value adding line* [59].

As figure 2.14 illustrates the value adding line will start from 100 % forecast accuracy and zero variation and it will end to zero forecast accuracy and 160% variation [59, 60]. The accuracy of the forecast exceeding a certain accuracy value and coefficient of variation is low enough; the current forecast should be, if not already, conducted with a sophisticated forecasting method [60]. For instance, when conducting forecasting a non-sophisticated forecasting method is easier to build than a sophisticated forecasting method. The reason why to evaluate the current forecasting method by Forecast value adding line is to reduce unnecessary work and also to improve forecast accuracy. Since, changing the forecasting method requires manual work unless there are several forecasting methods available.

To improve the forecast accuracy even more, several empirical studies have been done to discover if an aggregate forecast disaggregated into several forecasts have a better forecast accuracy than an individual forecasts combined into one combined forecast. According to D’Agostino and Bermingham (2011) some forecasts are the most accurate when disaggregate forecasts are combined during short period forecast and medium period forecast is made by aggregate figures instead of aggregate forecasts [61].

2.5 Summary of the Literature review

Companies have a dire need to work cost effectively throughout the value chain. Although there exists four different operating systems, MTS, ATO, MTO and ETO, they all share same goals. The goals are to serve customers by delivering the ordered product. A one of the difference of the aforementioned operation systems is lead time. This lead time can be reduced by several means. For instance, companies can conduct lean manufacturing, use S&OP, both or use another method. While the lean manufacturing reduce the waste, such as extra workload, and optimizing productivity by standardizing tasks, S&OP tries to optimize production and inventories to match the demand. The key task for S&OP is to work as a bridge between factories and sales units. The reason is to reduce over and under production and at the same time maximize sales. This will automatically have an impact on company's service level which will result to more new and permanent customers.

Commonly companies conduct the S&OP process as follows. There are four to five phases which are done a phase by phase. The S&OP process is a forward looking monthly process and the aforementioned phases are done in that time period. Usually the planning time frame for S&OP is from twelve to twenty-four months forward. An S&OP month can be divided into sales, operations and decision areas. The beginning of the month a demand plan is done by collecting inputs from sales units. In other words, sales units send their demand plan. The next phase is to split the demand and share it to factories, usually demand as a monetary value is translated to units. After this the factories receive the demand in units and make a plan to match it which the executive meeting, in the end of the month, will approve or disapprove.

The S&OP process uses forecasts to improve the demand planning. The demand planning, however, consists of quantitative or/and qualitative inputs which will form a consensus plan. The statistical forecasts use historical data as an input to project a forecast in to the future. The aforementioned input needs to be evaluated for its quality reasons. A good technique, for instance, is to conduct ABC/XYZ analysis which it will categorize products by their monetary value and volatility. The products, which have high monetary value and low volatility, are important to the company for the monetary importance but also important to forecasting process for low volatility. Since low volatility usually refers to a good forecastability.

There are two methods to create a prediction of the future, the qualitative and the quantitative methods. The qualitative method focuses on human opinions and intuitions which will be a base for a forecast. The quantitative method, however, focuses on statistical forecasting. It uses mathematical formulas to create a forecast. There formulas are, for example, Naïve, Moving averages, Trend projection, Brown, Holt's-Winters' and Bayesian methods. Each method creates a different forecast. Because there are several methods, it is important to choose the right method for the forecasting data. Usually MAPE is a good parameter to evaluate the suitability of a forecasting method.

Quality control is needed to evaluate how the forecasting data behaves. This can be conducted by using tracking signal method. The method uses MAD as a parameter and observes if the values exceeds the chosen control limits. These limits are set to the tracking signal by a user based on the knowledge that the limits should not be too tight or too big. The reason for setting the limits aforementioned way is to avoid looking or overlooking the forecast data or the forecasting method too often.

Kolassa (2009) introduces a value adding line which evaluates the suitability of the current forecasting method [59]. It uses the forecasting data's volatility and the forecast accuracy as parameters. It measures with these two parameters if the current forecasting method is too sophisticated for the forecasting process. The value adding line is recommended to use especially when the forecasting process is in the beginning.

3 METHODOLOGY AND THE CASE COMPANY ANALYSIS

This chapter introduces how the research is conducted based on literature review. The case company will provide the historical sales data for this research. The data has been chosen to the scope in order to improve the case company's S&OP forecasting and furthermore to improve supply chain management. However, the theory which is used during this S&OP improvement is strongly based on literature review in order to create the most optimal solution to the challenges which the case company is currently dealing with from the statistical forecasting point of view. The objectives introduced in chapter 1.3.1 remains the target for this analysis.

3.1 The Case Company

The case company operates in power and automation business. The operation environment is global. Customers are other companies, thus the business model is B2B. The case company operates and manufactures different products in different countries. Despite the fact that products are made globally the challenges with planning and forecasting are still the same regardless where the manufacture plant is located. During this thesis the key focus was to analyze historical sales data and discover trend and other forecasting related behavior in S&OP framework.

3.1.1 Products

There are several products made by the case company. However, the scope of the thesis covers only a few selected products. Therefore, only one product group was chosen for this research. The product group can be categorized into three different hierarchical levels.

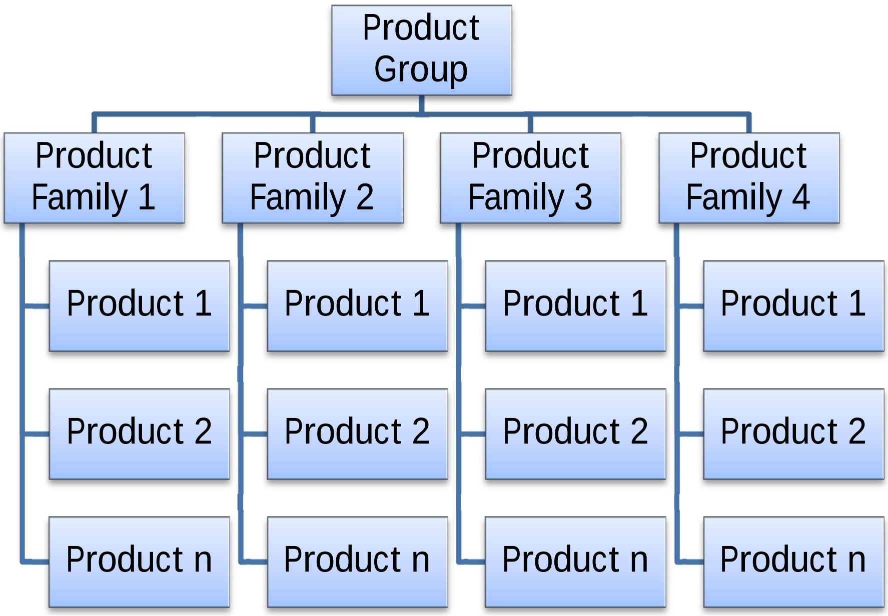

Figure 3.1 *The hierarchy of the case company's products for this thesis.*

As figure 3.1 shows, there are three hierarchies which will be utilized during this research. The highest hierarchy level is the product group level. It covers the data from products and their sales data. The most interesting hierarchy level for this thesis is the product family level because it is used by the demand plan process of the case company. Since the case company has numerous product families, only the four most important product families were chosen for this study. These product families were chosen beforehand by the case company. The last level is product level.

3.1.2 The Case Company's S&OP Demand planning process

Global Sales and Operations Planning has started in the case company's business unit. Therefore, the case company has decided to use product family 1 as a pilot. Thus, it is vital to develop this product family within the S&OP process. The case company can avoid problems and use already solved solutions that were discovered with the pilot product family 1. Although the idea is not to find faults or problems, this knowledge can be used to save time and effort in the future.

The case company's S&OP process is a monthly process. It starts, as chapter 2.2.1 presents, with demand planning and ends in the executive S&OP meeting. The case company S&OP process is a highly disciplined process. Each phase is done consecutively in their own time frame. The demand planning process starts firstly as follows: Global sales will provide guidance to a sales region about demand plan if needed. This phase usually takes one day. After the first day, demand planning process begins in the regional level. Region managers will do demand plans from their own regions. A region demand plan is done by using different techniques. Some regions rely on statistics, some on qualitative information and some on both. Because S&OP process is young in the case company, regions do not have a standard procedure to create a demand plan. Although different regions use different techniques, they provide adequate demand plan figures. The region demand planning phase of the demand plan process will take approximately three days. After that the global sales manager will review the demand plan and approve or disapprove it and modify the demand plan if necessary. At the end of the demand plan phase a reviewed demand plan meeting is held to go through the demand plans. After the demand plan review meeting the global sales manager will make modifications if necessary and approve the reviewed demand plan.

3.2 The research methodology for the empirical study

The transactional data of the thesis is collected from the company's own databases. The collected data was evaluated before it could be utilized further. Since the data also held all kinds of irrelevant information such as technical related figures, they were ignored or deleted before the research begun. It is worth of mentioning, that the process to discover the most suitable S&OP forecasting method for different product hierarchies was mostly iterative. The research method also included correlation analysis which will be introduced thoroughly in chapter 3.2.1. However, the idea was to recognize if sales records correlate with some other product's sales record or in the global business indexes.

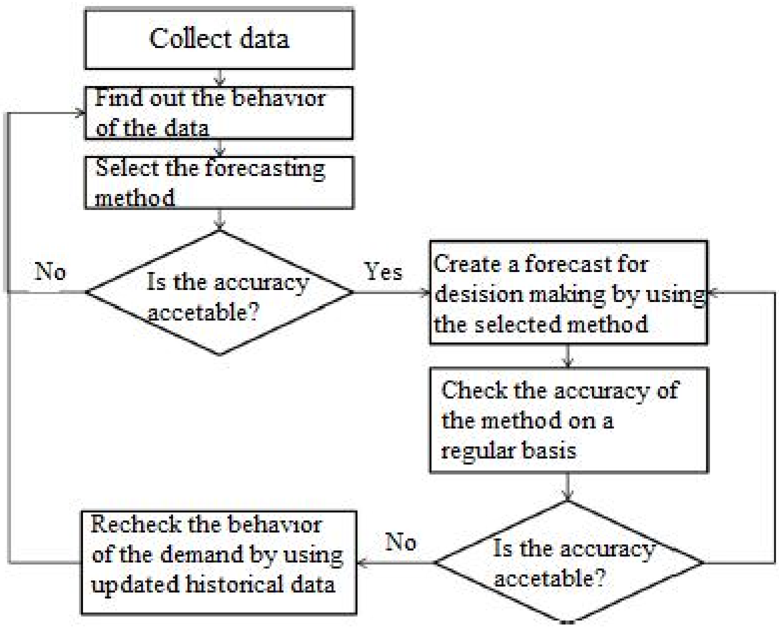

Figure 3.2 *Steps of creating a demand forecast* [62, p. 54].

Hanke (2001) recommends a pattern which would make a creation of a demand forecast easier and more reliable. As figure 3.2 points out, there are several steps to create a demand forecast. The first step is to collect the data. Obviously, this is the most important phase, since without the data there is not enough quantitative information to form a forecast. After the first step, the task is to study the data and find what kind of behavior the data holds. For instance, does the data have trends or seasonality, this phase provides results to the next step. Since there are several forecasting methods which work with different parameters, it is vital to understand the behavior of the data. The reason for this is that the selection will be based on this information. Regardless of the fact that the behavior is important, all the aforementioned forecasting methods are tested and errors are calculated. In other words, accuracy is tested for each method by using the same data. If the accuracy is not adequate enough, the next step is to return to analyze the behavior of the data. If the accuracy is good enough, the data can be inserted into the chosen forecasting method. In order to keep the accuracy within an acceptable level, the method should be tested on a regular basis. The reason for the accuracy drop is the behavior of the data. Since a forecasting method is made for a specific data behavior, such as seasonality or trends, the accuracy check is necessary to keep the forecasts as reliable as possible. [62, p. 54]

Since the behavior of the data defines the forecasting method, it is most important to find out if the historical sales data have seasonality, trends or other statistical behavior within the data. Especially since different forecasting methods give different forecasts. Thus, each and every forecast data has to be checked before entering that into a forecast formula. The reason for this is to get a good forecast quality. If one chooses a wrong method to create a forecast, the accuracy is low. A good example is to find suitable data which can be used for forecasting. For instance, forecastability can easily be tested by using the coefficient of variation formula.

$$Coefficient\ of\ variation = \frac{\sigma}{\mu}, \text{ where} \tag{1}$$

σ is standard deviation
μ is mean

Coefficient of variation will define how much the data oscillates from the average. Despite the fact that behavior is important to study before entering the data into the forecast formula, modern forecasting software has an ability to run the data through several forecasting methods and find the best solution without no significant data behavior study. After the software runs this program, it selects the best forecasting model calculating the forecast error MAPE. The aforementioned process is called Best fit or Pick best option as the subchapter 2.3.2.1 points out. Although this software exists, the thesis will not utilize this option. It is important to understand the volatility of the data, since it gives a fast answer, if the given data can work as a base for forecasting. If an automatic software is not available, all the work is done manually except calculation. Although there is not a best fit option available, a comparison is made between different forecasting methods for current forecasting data. That is the technique which will define which forecasting method is the most suitable for the case company’s business. Additionally the product families will be categorized similarly as figure 2.13 shows in order to conduct Lean-style forecasting. In other words, low volatility data is to be forecasted.

According to Mahmoud & Pegels (1989) a good forecasting method should be measured by its usability, how much information it provides, how costly it is to implement and what kind of results it gives during short and long time forecasts [51]. In this thesis, forecasting methods will be evaluated from the aforementioned perspectives.

	Method 1	Method 2	Method 3	Method 4	Method 5	Method 6
Usability						
Information						
Costs						
Short period forecast						
long period forecast						
Result						

Figure 3.3 *An evaluation chart for the forecasting methods* [63, p. 32].

Figure 3.3 shows the base chart for the evaluation of the forecasting methods. Each method will be evaluated by their usability, information, costs, short and long period forecast accuracy. Each section will be evaluated by a scale from zero to five. The method which has the highest score will be selected for the forecasting method for current sales data. This chart will evaluate six different forecasting methods. Usability refers to how easy or complex the method is. In other words, how difficult is the forecasting method to understand and utilize for testing. The information section will measure how much information the evaluated method provides. It will evaluate how much other additional information can be discovered from that specific forecasting method. This additional information can be seasonality or trends without studying seasonality and trend before entering the data into forecast models. The costs section will evaluate how much time and effort was used for building the forecasting method.

Usability is evaluated with the complexity of the forecast formula. If the forecast formula has more than one variable or sub formulas the score will get fewer points. For instance zero calculation gets the highest score and several sub formulas indicates that complexity increases. Points are given as follows:

- 5 points = zero complexity, no calculation
- 4 points = some complexity, simple formula
- 3 points = moderate complexity, some formulas
- 2 points = significant complexity, multiple formulas
- 1 point = very complex, complex mathematics and formulas

Cost will be evaluated by the time which was used to build the specific method. Each method's building process is timed. Evaluation is based on time windows as follows:

- 0 to 15 minutes = 5 points
- 15 to 30 minutes = 4 points
- 30 to 45 minutes = 3 points
- 45 to 60 minutes = 2 points
- More than 1 hour = 1 point

Both short and long period forecasting will be measured by MAPE value using its formula (22). The lowest MAPE will get five points and other points are equally divided from the second lowest MAPE to the worst. In other words points are distributed following.

- The lowest MAPE – 5 points
- Second lowest MAPE – 4 points
- Third lowest MAPE – 3 points
- Forth lowest MAPE – 2 points
- Fifth lowest MAPE – 1 point
- The highest MAPE – 0 points

All in all the evaluation chart will evaluate six forecasting methods and provide information which method is the most suitable for the historical sales data.

This evaluation is stressed with different factors. The reason for stressing is the case company's desire to look for the most accurate forecasting method, instead of concentrating on cost, usability or information. Therefore the stress is done as follows:

- Common attributes
    - Usability = 10%
    - Cost = 10%
    - Information = 10%
- Forecast accuracy
    - Long period forecast accuracy = 35%
    - Short period forecast accuracy = 35%

3.2.1 Correlation analysis

Companies and business is increasingly entangled together. Additionally business statistics are highly followed and shared on the internet. Therefore a typical assumption is that business indexes cover, on the internet, also the case company, suppliers and customers. The main reason for correlation analysis is to aid the S&OP demand planning process. However there is an opportunity to aid other stakeholders within the case company, for instance other business units. Yet, the main focus remains with the correlation analysis between the case company and global business indexes.

Since the case company has a high desire to improve S&OP processes, especially forecast quality, the secondary goal is to find if the historical sales data have a correlation or no correlation to other business units' data or some global indexes. Typically manufacturing indexes such as Organization for Economic Co-operation and Development (OECD) or Information and Forschung (Ifo) covers the case company's business, thus the research also include correlation analysis with these indexes. Introduction of Ifo and OECD are as follows:

- *"The CESifo Group, consisting of the Center for Economic Studies (CES), the Ifo Institute and the CESifo GmbH (Munich Society for the Promotion of Economic Research) is a research group unique in Europe in the area of economic research. It combines the theoretically oriented economic research of the university with the empirical work of a leading Economic research institute and places this combination in an international environment."* [64]
- *"OECD is an international organisation helping governments tackle the economic, social and governance challenges of a globalised economy."* [65]

Firstly the comparison will begin with data analysis of the global sales indexes. This analysis will determine how the correlation analysis will be done. It is important to know how two data sources can be measured together. Since there is a high probability that there is not full correlation constantly with the case company's sales data and global indexes, the next phase is to find the best correlation result by comparing the statistics with different time delays. For example, January's trend in global index is the same as March's trend in sales figures. If valid, one can determine that with some delay the correlation is the highest with current parameters.

The correlation analysis will be conducted by comparing trends of the historical sales data and global business indexes. Since it is more important for the case company to understand if their sales data is following global indexes instead of the other way around, the correlation analysis is done as follows. The first comparison will be calculated using a one month delay. For instance January value of a global index will be compared to the case company February value. The second comparison will be calculated using a two month delay. For example January value of a global index will be compared to the case company March value. The third comparison will be calculated using a three month delay. For instance January value of a global index will be compared to the case company April value.

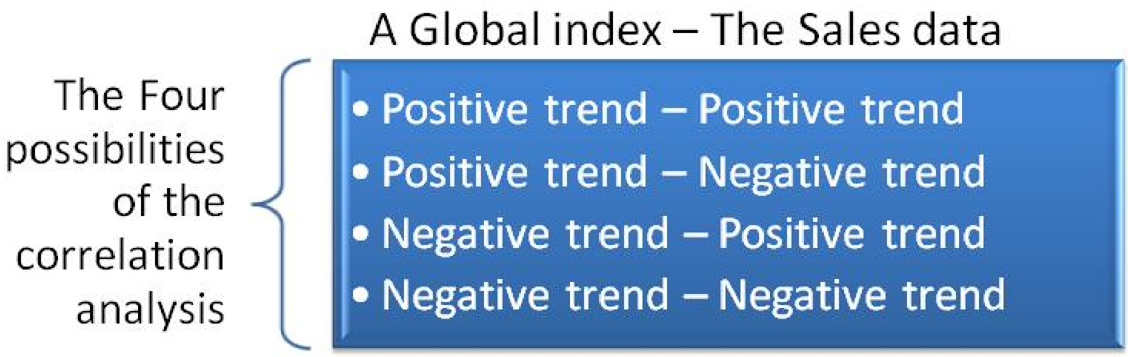

Figure 3.4 *The four possibilities for comparing trends.*

As figure 3.4 shows there are four different result possibilities. Each comparison will have one of the above results. If the values have a full match, either positive or negative, it correlates. If the values have different trend, there are no correlation.

3.3 Key Performance Indicators

A quality of a forecast plays a key role in the business world. It is important to follow the demand planning process of S&OP and measure the performance. A common KPI is forecast accuracy which can be measure by using MAPE. The accuracy can be calculated utilizing long, short and current period data. A good way to illustrate the forecast accuracy is to plot the accuracy on a monthly basis as a graph. This will illustrate how good the accuracy is. In addition, as chapter 2.3.5 introduces, the case company should track the behavior of the forecast data. A good measure is to set control limits which will indicate if the current forecast is not working correctly. For this thesis the tracking signal and its formula (19) will be made to evaluate how well the current demand plan for product family 1 has matched to actual demand. The reason why product family 1 is chosen as the pilot is that it has been in the scope of the case company's S&OP the longest. The control limits are chosen as by using dynamic standard deviation of four available months' forecast error or demand plan error, however in this thesis the limits will be calculated only once to demonstrate the utilization. The purpose for setting the control limits to this way is to avoid overlooking the demand plan accuracy too often, especially since the S&OP has recently started in the case company and the expected accuracy is not high. Thus the limits are multiplied by a safety factor, for instance a value of 1.2, to avoid aforementioned problems.

Based on the literature review a value adding line will be created to evaluate if the winner of the forecast evaluation is too sophisticated for the case company's business. The idea is to calculate variation by using coefficient of variation (1) and short term forecast accuracy and to plot it on a graph and evaluate the suitability. As the literature shows, if the value exceeds the forecast value adding line, the forecast should be a sophisticated method. If not, the method should be less sophisticated.

Demand plan accuracy should be also evaluated throughout the S&OP time frame. Therefore it is good to collect the historical demand plans and compare how well the past plans corresponded with the end result. A good technique is to build a waterfall analysis. This analysis merely collects the demand plans and grants a comparison with the actuals. With this knowledge the case company can estimate how much the demand forecast will have error in the future demand plans. In other words, the case company can expect a certain error for each planned month.

4 IMPROVING S&OP DEMAND PLANNING

This chapter holds the results of the research and shows how the empirical study is done. The research has been an iterative process. The idea was to recognize and improve forecasting methods for certain products from different levels of product hierarchy. One key goal was also to find and analyze demand trends for different product hierarchies, find correlations from other business indexes and find solutions to research questions.

4.1 Recognition of the behavior of the data

The search for the best forecasting method for the case company began by a data analysis. The idea was to recognize data behavior. The need for data analysis is simple. One needs to know what kind of data is about to be forecasted. Additionally some data behavior, such as trends or seasonality, can reveal that some forecasting methods are not suitable for certain kinds of data.

Before the data analysis could be conducted the data must be available. The given data was historical sales data of the case company. The sales data was incomplete for the test. In other words there was a lot of irrelevant information. This irrelevant data was excluded from the analysis. Additionally some data were invalid according to the case company. The data covered all product families of the scope and held the necessary information to conduct tests of the analysis. Since the data was raw, it required a lot of organizing and cleaning in order to start the research. From the thesis point of view, the data had a huge amount of irrelevant information and attributes in the data. Therefore, the data was reorganized before the tests were conducted. Some of the information is mere technical information which is not usable for creating forecasts. The reason for limiting the data from all attributes was to make the research process faster and reliable. Since the focus is to find the best possible forecasting method for the case company's demand plan process, the need for excluding some technical attributes is necessary. Additionally the literature review did not recommend using various attributes with the demand forecasting. Nonetheless, aforementioned information about excluded attributes could be utilized for finding correlations from global business indexes.

As mentioned before the process of building a forecast for the case company begins from collecting the data. Since the case company already provided the data, the next step is to start evaluating the data and recognizing what kind of behavior the data holds.

Typical behavior for a sales data is seasonality, data variation and trends. These factors are vital to find if some forecasting methods are to be utilized.

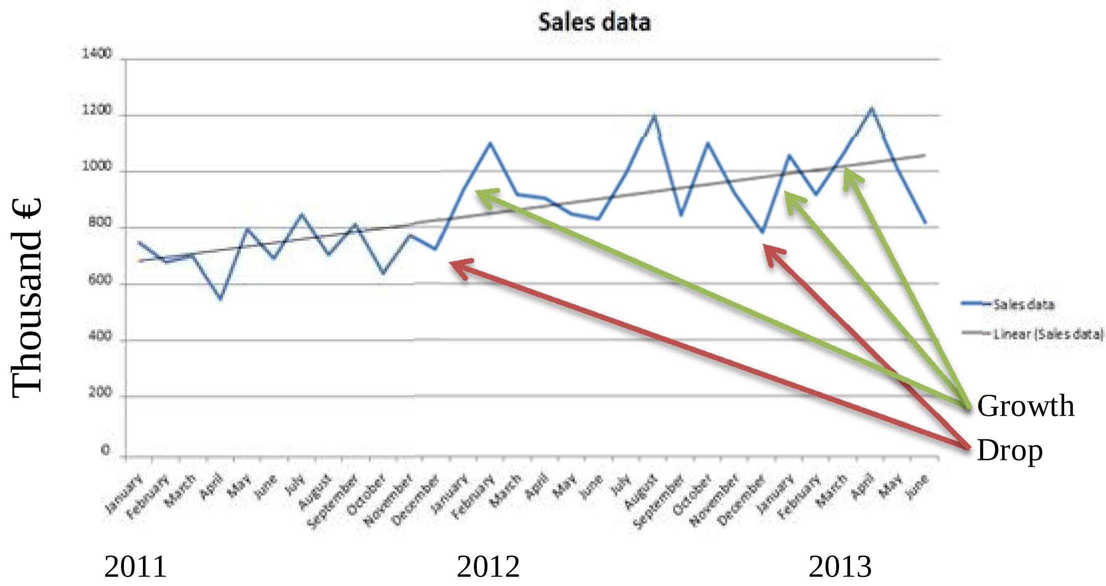

Figure 4.1 *The behavior of the historical sales data of the product group.*

Figure 4.1 is a graphical projection of the behavior of a historical sales data. As the figure shows there is a steadily growing trend. There is also some seasonality within the sales data. Especially at the end of the year sales tend to decrease and at the beginning of the year tend to increase. Therefore, some forecasting methods can be excluded based on aforementioned behavior, such as Holt's two parameters method. The reason for excluding Holt's method is that it works better without seasonality behavior. However, Holt's-Winters' method covers both aforementioned behaviors. Despite the fact that Exponential smoothing methods are relevant for these tests, the need for testing similar methods is pointless. However, if one observes other product hierarchies, such as product hierarchy level, some of the behavior is not visible or there is none. On the other edge of the hierarchy is the product group level where all products are aggregated together and the behavior of the data is more stable and will not necessarily need a sophisticated forecasting method such as Holt's-Winters'.

4.1.1 Choosing the parameters

From the case company's point of view the research needs to give a result which benefits the company's business. Therefore the forecast tests will be made to all product hierarchies as figure 3.1 indicates. The tests will be conducted one hierarchy level at a time. The first hierarchy level which is chosen to do piloting for the tests is the product level. Although it is not currently used by the S&OP of the case company it is wise to recognize if the lowest level can be forecasted and that information can be used for optimizing inventories. The highest focus for the search for the best forecasting method will be on product family level since this it is used in the case company’s S&OP process.

Figure 3.1 shows that there are several hierarchy levels which need to be tested. Although there are several different hierarchy levels, they all share a same data format which made the test more convenient. The focus is to use time, quantity and monetary value as parameters. These three parameters can be utilized to create a basic forecast.

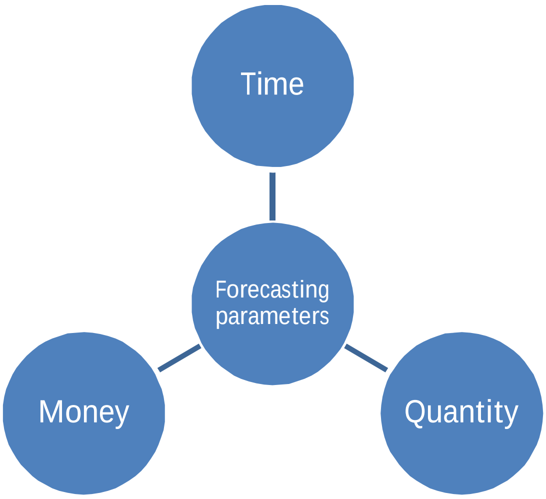

Figure 4.2 *Chosen parameters from the forecast data.*

However, although these three different parameters, showed in figure 4.2, can be used for forecasting, the key parameters for this research are the time and money parameters. Since demand planning tend to focus on these parameters. Additionally the table 4.1 will show that the volatility is higher for the quantity than for the money. The analysis consisted of data analysis, where every product hierarchy level was analyzed from volatility perspective. Since the typical time frame is a month, the basic assumption is that volatility tends to increase when product hierarchy grows in depth.

Figure 4.3 *A Forecasting difficulty matrix created for the thesis by the author.*

Figure 4.3 illustrates the volatility level in a product hierarchy and time matrix. As one can determine from the graph, making a reliable forecast gets harder when approaching the top right corner. However, in the case company, S&OP tend to focus in y-axis on product family level and in x-axis the focus is on month. The frame size level will not be utilized during the research due to a reason that it is not used by the demand planning process of the case company. Although the base idea of S&OP is to balance aggregate supply and demand, S&OP does not conduct factory level daily planning since it is more of a scheduling than planning. Therefore, the lowest hierarchy level will not be simulated with the forecasting methods. In addition, according to figure 4.3 statistical forecasting is difficult when operating in product or frame size levels.

As the literature review explains, calculating Coefficient of variation (1) of the data is a good technique to measure if the forecast data is good enough for creating a forecast. If the calculated value is above 100%, the deviation of the data is more than the average, thus forecast accuracy tends to decrease. Before forecast tests can be conducted, one needs to calculate the variability for the rest of the hierarchies. In chapter 2.4, variability should be categorized as follows. The low variability is between 0 and 75% which can be forecast easily. Moderate variability is considered to be from 75% to 133% and high variability is more than 133%.

Table 4.1 holds the results of the calculations of variability. The values are calculated by using coefficient of variation formula (1).

Table 4.1 *The results of coefficient of variation analysis.*

	Product Group	Product family 1	Product family 2	Product family 3	Product family 4
30 months (money)	16 %	25 %	15 %	55 %	49 %
30 months (quantity)	29 %	37 %	47 %	70 %	56 %

The result shows that all of these hierarchies have low variability when using money and time as parameters. This result indicates that each product hierarchy is good enough to make a forecast since the low variability when using time and money combination. The variability is higher for quantity and time combination. Thus money and time parameters are better for forecasting. The appendix 3 indicates that variability increases when observing the lowest level of the hierarchy. In order to conduct forecasting at this level of hierarchy, a calculated categorization should be used. That method for this categorization is used in the next chapter.

4.2 Segmenting the products

S&OP requires forecasts, however it is important to recognize which data is good enough for forecasting. As previously showed in the table 4.1, aggregate data is stable from a volatility perspective. Thus, this data is good enough for forecasting. As mentioned before, if the values are under 75%, the data series have low variability. Even though there exists forecasting methods that are able to form a forecast from data with a relatively high volatility, forecast accuracy will be significantly lower compared to forecasts made on low volatility data. The original research question states that the case company desires to categorize products in the case company's business. A proposed solution for categorization is an ABC-XYZ analysis which is introduced in chapter 2.4.

The aforementioned analysis is a combination of ABC analysis, where products are segmented by their monetary importance, a relative proportion of the product's price, into A, B and C class and XYZ products, which represent the volatility of the products. A products cover 75 percent of the business, B products 20 percent of the business and C products cover the last 5 percent of the business. X products have volatility between 0 and 75 percent, Y products have volatility between 75 and 133 percent and Z products have volatility greater than 133 percent.

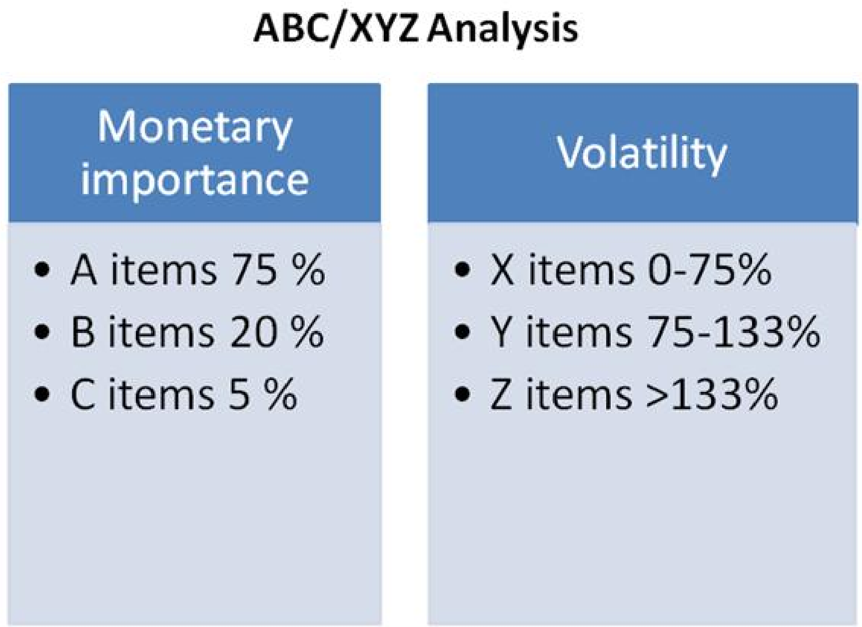

Figure 4.4 *The ABC-XYZ analysis* [54].

Figure 4.4 explains how the products can be categorized. Obviously, A products are the most important products from the case company's perspective since they cover the greatest share of the monetary volume. However from a statistical forecasting perspective X products are the most desired products, since the volatility is relatively low. Therefore products are classified into nine categories. This analysis is done only for the products which the case company recognizes to need for a categorization. As figure 3.1 shows there are several levels how the data is constructed. The case company has chosen the lowest level of the product hierarchy for this analysis, highlighted in the figure 4.5. The scope of this analysis is Europe's stock and production products and the time frame are the first six months of the year 2013.

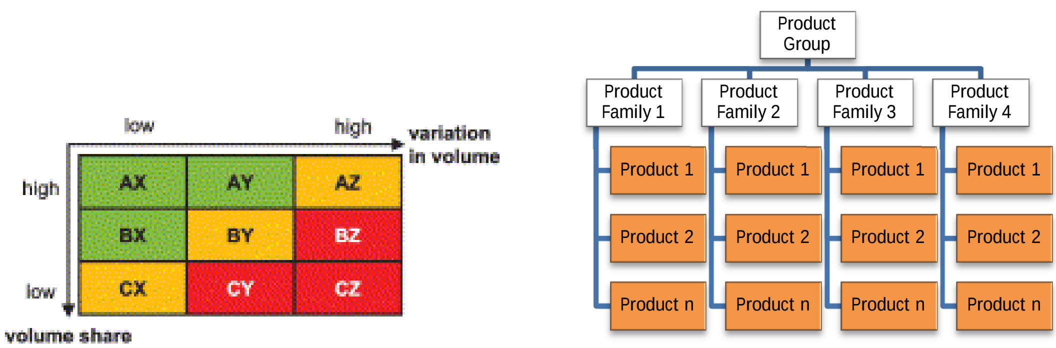

Figure 4.5 *The categorization of the ABC/XYZ analysis and the chosen hierarchy level* [54].

The following tables are based on the categorization in figure 4.5. These tables have been divided into three different groups. The color of the first group is green. The green color marks the products which should be included in the forecasting process since products have a high monetary value and low variability. Yellow color marks products which could be included to the forecasting process since these products have moderate volatility or do not have high monetary value compared to other products. Red color subscribes products which should be purely left out from the statistical forecasting process because these products are not easy to forecast due to high volatility or do not have monetary importance compared to other products. If, however, these products are to be forecasted the expect accuracy is low. Although, red products should be left out from the forecasting process, these products could be business enablers. Thus, the importance of the red products should not be understated.

Table 4.2 *The results of ABC/XYZ analysis for product family 1.*

Product family 1	A	B	C	SUM XYZ
X	7 % (73)	9 % (94)	5 % (49)	21 % (216)
Y	4 % (39)	9 % (90)	14 % (142)	27 % (271)
Z	2 % (23)	10 % (103)	40 % (407)	52 % (533)
SUM ABC	13 % (135)	28 % (287)	59 % (598)	100 % (1020)

As one can see from the table 4.2 there are 7 percent of the product family 1 products which can be easily forecasted and have high monetary value. Although several products can be forecasted, the majority of the products are classified as Z products which have a high variability resulting in low forecastability. More than half of the products belong to Z products which have high variability. For these products the case company has, for instance, to keep safety stocks in order to match customers' infrequent demands in order to have a good service level or remove a stock profile from these products which will result in lower service level and lower costs.

Products of the Product family 2 behave mostly the same as the product family 1's products.

Table 4.3 *The results of ABC/XYZ analysis for product family 2.*

Product family 2	A	B	C	SUM XYZ
X	11 % (113)	16 % (171)	5 % (57)	32 % (341)
Y	2 % (22)	8 % (89)	11 % (119)	22 % (230)
Z	1 % (6)	5 % (58)	40 % (420)	46 % (484)
SUM ABC	13 % (141)	30 % (318)	56 % (596)	100 % (1055)

As one can observe from the table 4.2 and 4.3 these two product families' data behaves similarly. Product family 2 has a higher percentage of X products than product family 1. Additionally, the majority of A products can be easily forecasted. This can also be said for B products. C products, however, have high variability.

Table 4.4 *The results of ABC/XYZ analysis for product family 3.*

Product family 3	A	B	C	SUM XYZ
X	8 % (25)	15 % (46)	15 % (47)	38 % (118)
Y	4 % (11)	5 % (14)	20 % (63)	28 % (89)
Z	0 % (0)	5 % (15)	29 % (91)	34 % (107)
SUM ABC	11 % (36)	25 % (77)	64 % (201)	100 % (314)

Table 4.4 indicates that product family 3 has almost equally divided XYZ products. This product family had the least number of products. Compared to other product families, this product's products have lower variability than the other products. Thus, generally product family 3 is the most suitable for statistical forecasting, since these products have a good forecast profile. In this case the profile means low variability.

Table 4.5 *The results of ABC/XYZ analysis for product family 4.*

Product family 4	A	B	C	SUM XYZ
X	13 % (68)	17 % (88)	6 % (29)	35 % (185)
Y	4 % (21)	10 % (54)	13 % (66)	27 % (141)
Z	1 % (6)	5 % (25)	32 % (169)	38 % (200)
SUM ABC	18 % (95)	32 % (167)	50 % (264)	100 % (526)

Product family 4 has the highest portion of AX products of all aforementioned product families. The result, in table 4.5, indicates that statistical forecasting is the most suitable for product family 4 A products.

The reason for excluding higher product hierarchies from ABC/XYZ analysis was presented in table 4.1. This table states that higher hierarchies have more stable variability, thus all higher hierarchies belong to X group. Additionally the case company's desire was to analyze only this product hierarchy level by the aforementioned analysis. This calculated information enables the case company to conduct low volatility forecasting for the four product families since volatility is low enough for S&OP statistical forecasting when utilizing X products.

Since C products are the majority in every product family, the case company should exclude more than half of the products from statistical forecasting and keep a safety stock for those products in order to keep the service level high. Another option is to increase lead time and reduce inventory for those products. Despite the fact that the case company conducts ETO, MTO and ATO manufacturing, several products of the ABC/XYZ belongs to MTS which are high runners comparing to other product families out side of the scope. Thus in the XYZ analysis these high runner products belongs, without exception, to A group and according to the above tables they are with high probability X products.

This ABC/XYZ analysis revealed that more than 60 percent of the A products can be statistically forecasted. Therefore it can be assumed that 60 percent of the A products have an opportunity to reduce inventories and to optimize production to match the demand. This will eventually result to less capital consuming inventories and a better service level. The reason for this is that statistical forecasting is an enabler to manufacture products at the right time and in the right amount to match the demand.

4.3 Selection of the statistical forecasting methods for the tests

As chapter 2 introduced, there are several forecasting methods which can be used to create a forecast. However, forecasts have to be tested and analyzed in order to create a reliable and realistic forecast for certain products or businesses. This usually requires manual testing. After testing, the next step is analyzing and finding the margin of error. Chapter 2.5 introduces some mathematical error formulas which could be good indicators to select the most suitable forecasting method.

For this thesis the key interest is to seek the best possible forecast technique for the case company's products. Therefore, several tests will be done to find the best forecasting method. However, the selected forecasting techniques, which are to be tested, are based on their difference from each other which chapter 2 introduced. The general idea is to test dissimilar forecasting methods. However, only the following six were chosen, since, according to the literature review, these six represent different forecasting methods. The reason for this is that the case company does not have the knowledge of what kind of forecasting method could be the best. The selected forecasting methods for testing are:

- Naïve
- Holt's-Winters'
- Brown's model
- Bayesian
- Trend projection
- Moving averages

As chapter 2 introduced, all of these techniques are quantitative techniques. However, if the selected forecast for this business is to be improved further, there needs to be at least some qualitative methods included. Although this has to be acknowledged, it is excluded from the research because it is not in does not fit in the scope of the thesis. In addition it is not statistical information and it cannot be improved by using mathematical formulas. As chapter 2.3.3 explains, qualitative forecasts are based on human judgments and predictions.

While forecasting, one needs to decide how often forecasting is conducted. In other words, one needs to set suitable time period for forecasting. Commonly, these frequencies are:

- Year
- Quarter
- Month
- Week
- Day

Although, it is possible to forecast on a daily basis and make a detailed forecast, the forecasting process gets more difficult, as showed in figure 4.3, if the frequencies are shorter compared to larger such as a month or a year. Additionally, as chapter 2.3.1 introduces, the S&OP process concentrates on planning on the mid- and long-term time frame and more using a monthly cycle. Therefore, it is important to calculate coefficient of variation of the data in different time frequencies. This result gives a vital information which can be used as a base for forecasting if one has to create a forecast using other than a month. Commonly S&OP forecasts use a monthly frequency. It is used to make plans for mid or long term time period.

4.4 Results of the tests

The important step for forecasting is to choose the forecasting data. Since money and time parameters have lower variability as the table 4.1 shows, the tests will utilize these parameters since the forecasting accuracy is to expect to be better while volatility is lower. In addition, according to the volatility limits of the XYZ analysis in figure 4.4 and the results in table 4.1, both product group and product families share the same volatility level X, and all of them could be chosen for the upcoming tests. However, the chosen product hierarchy is product group level, since some of the forecast techniques, in chapter 4.1, are excluded from the tests based on the behavior of product group data.

The tests began by building the chosen forecasting methods. In order to conduct the forecast tests, the simulator was created for this purpose. The simulator was built with Excel and all the six forecasting methods were included to this simulator. This Excel based forecast generator calculates and optimizes particularly the parameters of the sophisticated forecasting methods. It minimizes MAPE value for more sophisticated forecasting methods and finds the parameters for to get the smallest MAPE. The reason to do this is since more sophisticated forecasting methods require parameter optimization. From a time and effort perspective, the more sophisticated methods require more work than the simpler forecasting methods.

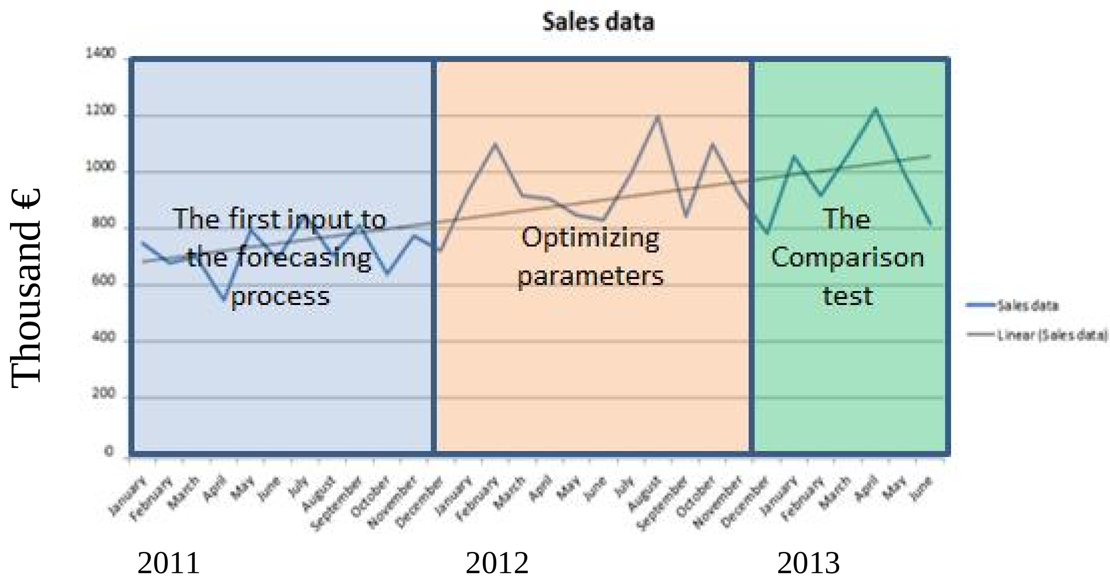

Figure 4.6 *The path how to use and optimize the sophisticated forecasting methods.*

The figure 4.6 illustrates how the sophisticated methods are used during the tests. After the forecasting models were built, the tests began. First results founded a base which worked as a reference for other forecast tests. Since the project was iterative, the first results were an important first step due to the reason that sophisticated forecasting methods require optimization. Although some of the forecasting methods are simple and they provide the best results only when forecasting short time periods which do not require optimization. The information about these forecasts' unsuitableness is important knowledge. Nevertheless, these simple forecasting models were built, although expected results were clear before anything was done due to the findings in chapter 4.1.

Usability, information and costs are similar during the tests; therefore the evaluation for these attributes is done only once. Obviously, simple forecasting methods were easier to build since these methods have fewer variables. These methods are Naïve, Trend projection, Moving averages and Bayesian. Bayesian, however, is easy to build if there are already four necessary methods available. Since the Bayesian method was wisely built last, it turned out to be easy. From a usability perspective all of the aforementioned methods are easy to use. If the Bayesian method was built first, it would have been the most time consuming method. Although sophisticated methods require more mathematical understanding they all resulted in being easy to use. Information, however, had different results compared to the aforementioned two. As previously introduced in chapter 2.3.2 there are dramatically high differences between sophisticated and simple forecasting methods. For instance Holt's-Winters' method recognizes trends, seasonality and level of the historical data whilst Naïve or Moving averages are lacking these kinds of abilities. The expected information results would favor more sophistical methods.

As one can determine Naïve method is simple. It does not contain complexity like the other forecasting methods. Therefore it got the highest score as figure 4.6 shows. Moving averages, Bayesian and Trend projection have some calculation, but do not have complexity high enough to decrease the score more. Thus the score for those methods are four. Holt's-Winters' and Brown's methods have sub formulas to improve forecast efficiency. For that reason the complexity increases and the score is three for these forecasting methods.

Naïve method was the fastest and effortless to build. Building this method took only a short amount of time. Trend projection, Moving averages and Bayesian consumed double the amount compared to Naïve. Because of the complexity of more sophisticated methods Brown and Holt's-Winters' methods consumed the most amount of time. The results are:

- Naïve = 10 minutes
- Trend projection = 20 minutes
- Moving averages = 20 minutes
- Bayesian = 20 minutes
- Brown = 40 minutes
- Holt's-Winters' = 40 minutes

	Naive	Holt's-Winters'	Brown	Bayesian	Trend projection	Moving averages
Usability	5	3	3	4	4	4
Information	1	5	2	3	2	2
Costs	5	3	3	4	4	4
Result	11	11	8	11	10	10

Figure 4.7 *The results of the common attributes.*

As figure 4.7 shows all of the forecasting methods have relatively high score. These results indicate that selected forecasting methods are well chosen for the upcoming tests.

Since demand planning is a monthly process in S&OP which look 18 months forward, forecasts are updated every month. Therefore it is important to calculate and measure which of the chosen forecasting methods is the best for short and long period forecasting, since forecasts need to be as reliable as possible throughout the time frame of the S&OP process. The short period forecasts are created every new month and they concentrate to forecast the next month's value. In other words, they are updated every time when a new month is available for forecasting. These forecasts use historical sales data beginning the last actual figures available from January 2011 as an input to forecasting. The long period forecasts, instead, are created only once and these forecasts are not updated again during the test. Afterwards the long term forecasts are compared to the actual figures. Again the forecasts, showed in figures 4.8 and 4.9, are using actual figures from the years 2011 and 2012 to create forecasts for the year 2013's first six months and these figures are compared into actual values.

Since the historical sales data is only 30 months beginning from year 2011, the optimization and data gathering period for more sophisticated methods is 24 months as the figure 4.6 illustrates. The reason for this selection is that more sophisticated methods require at least two years of data to form an optimized forecast. Therefore the time frame for this comparison is the first six months beginning from the year 2013 showed in figures 4.6, 4.8 and 4.9. This data should give the best possible result for the forecasting method evaluation. In the results, errors are calculated by using MFE (23) to find the mean forecast error from the values shown next. MAPE (22) is also calculated to find the forecast percent for comparison. The methods and the formulas for this test were:

- Naïve (2)
- Trend projection (3)
- Moving averages (4)
- Holt's-Winters' (9)
- Brown (13)
- Bayesian (18)

Actual and Forecast values						
Actuals	Naive	Holt's-Winters'	Brown	Bayesian	Trend projection	Moving averages
1 069	812	1 176	839	866	908	835
1 011	812	1 163	839	861	916	838
1 119	812	1 399	839	916	924	835
1 145	812	1 328	840	897	932	839
990	812	1 168	843	856	940	845
862	812	896	847	787	948	851
Long period forecast Error calculation						
	Naive	Holt's-Winters'	Brown	Bayesian	Trend projection	Moving averages
Future period 1 error	258	-107	230	137	162	234
Future period 2 error	200	51	172	104	95	173
Future period 3 error	307	-90	280	174	195	284
Future period 4 error	333	183	305	167	213	306
Future period 5 error	179	-178	147	49	50	146
Future period 6 error	50	-34	15	-15	-86	11
MFE	221	-29	192	103	105	192
	Naive	Holt's-Winters'	Brown	Bayesian	Trend projection	Moving averages
Future period 1 error %	32 %	10 %	27 %	15 %	18 %	28 %
Future period 2 error %	25 %	5 %	21 %	12 %	10 %	21 %
Future period 3 error %	38 %	8 %	33 %	18 %	21 %	34 %
Future period 4 error %	41 %	16 %	36 %	17 %	23 %	36 %
Future period 5 error %	22 %	18 %	17 %	5 %	5 %	17 %
Future period 6 error %	6 %	4 %	2 %	2 %	9 %	1 %
MAPE	27 %	10 %	23 %	11 %	14 %	23 %

Figure 4.8 *The long period forecast results.*

Figure 4.8 points out that Holt's-Winters' method is the most suitable method for long period forecasting. Although, the forecast time frame was relatively short compared to the scope of S&OP process, the result was conclusive evidence that a more sophisticated method is the best forecasting method for this data. The worst method was Naïve method. Since the aforementioned method was using the last available figures as the forecast value, it had the highest MAPE of all six forecasting methods. The aforementioned results support the literature review chapter 2.3.2 that Naïve method is not made for long period forecasting and it should not be used as such.

Actual and Forecast values						
Actuals	Naive	Holt's-Winters'	Brown	Bayesian	Trend projection	Moving averages
1 069	812	1 176	839	982	1 038	901
1 011	1 069	1 129	1 063	996	882	942
1 119	1 011	1 047	1 028	976	908	964
1 145	1 119	1 047	1 028	976	908	1 067
990	1 149	1 084	1 032	996	916	1 092
862	990	905	1 041	1 002	924	1 085
Short period forecast Error calculation						
	Naive	Holt's-Winters'	Brown	Bayesian	Trend projection	Moving averages
Future period 1 error	258	-107	230	88	31	168
Future period 2 error	-58	-117	-52	16	129	70
Future period 3 error	108	72	91	143	211	155
Future period 4 error	26	98	116	169	237	78
Future period 5 error	-158	-94	-42	-5	74	-101
Future period 6 error	-128	-43	-179	-140	-62	-223
MFE	8	-32	27	45	104	24
	Naive	Holt's-Winters'	Brown	Bayesian	Trend projection	Moving averages
Future period 1 error %	32 %	10 %	27 %	9 %	3 %	19 %
Future period 2 error %	5 %	10 %	5 %	2 %	15 %	11 %
Future period 3 error %	11 %	7 %	9 %	15 %	23 %	22 %
Future period 4 error %	2 %	9 %	11 %	17 %	26 %	24 %
Future period 5 error %	16 %	9 %	4 %	1 %	8 %	4 %
Future period 6 error %	13 %	5 %	17 %	14 %	7 %	9 %
MAPE	13 %	8 %	12 %	9 %	14 %	15 %

Figure 4.9 *The short period forecast results.*

Figure 4.9 points out that Holt's-Winters' was also the best method for the short period data series which was used to create this forecast. Comparing the results with long period forecast results; Naïve is clearly a short period forecasting method. Surprisingly Moving averages had the worst accuracy during this test. The reason for this phenomenon was actual data. The data was steadily rising and suddenly it dropped dramatically. Therefore average calculation was constantly highly off from the actuals.

In conclusion, the forecast tests clearly shows that for this data the best method for calculating short and long period forecasting is Holt's-Winters' three parameter method. Since, as chapter 2.3.1 introduces, it recognizes trends, seasonality and levels of the data. Therefore it can be utilized for further forecasting for aforementioned data series. The short period forecast results for the evaluation chart:

- Holt's-Winters' – 5 points
- Bayesian – 4 points
- Brown – 3 points
- Naïve – 2 points
- Trend projection – 1 point
- Moving averages – 0 points

The long period forecast results for the evaluation chart:

- Holt’s-Winters’ – 5 points
- Bayesian – 4 points
- Trend projection – 3 points
- Brown – 2 points
- Moving averages – 2 point
- Naïve – 0 points

Since Brown and Moving averages got the same MAPE, both of the methods get two points each.

	Naive	Holt's-Winters'	Brown	Bayesian	Trend projection	Moving averages
Usability	0,5	0,3	0,3	0,4	0,4	0,4
Information	0,1	0,5	0,2	0,3	0,2	0,2
Costs	0,5	0,3	0,3	0,4	0,4	0,4
Short period forecast	0,7	1,75	1,05	1,4	0,35	0,0
long period forecast	0,0	1,75	0,7	1,4	1,05	0,7
Result	1,8	4,6	2,55	3.9	2.4	1.7

Figure 4.10 *The complete evaluation chart after stress.*

Figure 4.10 shows the full results of the forecast tests. According to the evaluation chart, Holt’s-Winters’ is the best method for the sales data. Although Moving averages was the last of the six forecasting methods, it is still a good forecasting method for data which does not require a sophisticated forecasting method.

4.5 Comparison against business indexes

As chapter 3.2.1 stated, the case company has an interest to find out if the historical sales data correlates with other data sources such as global business indexes. There are several global business indexes available throughout the internet. The most usable indexes for this business are OECD and Ifo institute indexes. These indexes correspond with global economy, business climate and manufacturing. However, there are only a couple of relevant indexes which can be utilized with this thesis. Although Ifo and OECD provide several indexes there are other many usable indexes. When analyzing indexes it needs to be acknowledged that the indexes are not completely valid for this business. Selected indexes are combinations from all around the world from all the companies which can match the criteria of the index. Since there are no other indexes available, the comparison needs to cope with available indexes with a strong critical view. Despite the fact that the aforementioned indexes do not only cover the case company's business, the idea of this analysis is to find a correlation between the case company's sales data and these indexes.

The global business indexes use a measurement, which is not directly comparable between the case company's sales figures. These indexes are scaled to average values which can be used for recognizing trends. Therefore, a good comparison technique is to measure monthly trends. The analysis is done by comparing the sales data and business indexes together with one, two and three months delay. The time frame for correlation analysis was the first six months of the year 2013, since the quality of the case company's data is valid for that time period. The correlation analysis was made between Ifo statistics, OECD index and a couple of product hierarchy level sales figures - product group and family level.

One month delay with OECD index

Date	OECD Germany		Product Group		Product family 1
2012/12	Positive trend				
2013/1	Positive trend	Match	Positive trend	Match	Positive trend
2013/2	Positive trend	Match	Positive trend	No Match	Negative trend
2013/3	Positive trend	Match	Positive trend	Match	Positive trend
2013/4	Positive trend	No Match	Negative trend	No Match	Negative trend
2013/5	Positive trend	No Match	Negative trend	No Match	Negative trend
2013/6	Positive trend	Match	Positive trend	Match	Positive trend
		4/6	Match	3/6	Match

Two months delay with OECD index

Date	OECD Germany		Product Group		Product family 1
2012/12	Positive trend				
2013/1	Positive trend		Positive trend		Positive trend
2013/2	Positive trend	Match	Positive trend	No Match	Negative trend
2013/3	Positive trend	Match	Positive trend	Match	Positive trend
2013/4	Positive trend	No Match	Negative trend	No Match	Negative trend
2013/5	Positive trend	No Match	Negative trend	No Match	Negative trend
2013/6	Positive trend	Match	Positive trend	Match	Positive trend
		3/5	Match	2/5	Match

Three months delay with OECD index

Date	OECD Germany		Product Group		Product family 1
2012/12	Positive trend				
2013/1	Positive trend		Positive trend		Positive trend
2013/2	Positive trend		Positive trend		Negative trend
2013/3	Positive trend	Match	Positive trend	Match	Positive trend
2013/4	Positive trend	No Match	Negative trend	No Match	Negative trend
2013/5	Positive trend	No Match	Negative trend	No Match	Negative trend
2013/6	Positive trend	Match	Positive trend	Match	Positive trend
		2/4	Match	2/4	Match

Figure 4.11 *The results of correlation analysis with OECD index.*

Figure 4.11 shows the results of the correlation analysis between OECD index and the sales data. The results turn out to be medium correlation with all delays. The strongest correlation was one month delay with product group hierarchy. Although the correlation was 4/6 of the months, a strong correlation cannot be determined. The rest of the results in figure 4.11 show neither zero nor strong correlation.

One month delay with Ifo index					
Date	Ifo index		Product Group		Product family 1
2012/12	Positive trend				
2013/1	Positive trend	Match	Positive trend	Match	Positive trend
2013/2	Positive trend	Match	Positive trend	No Match	Negative trend
2013/3	Negative trend	Match	Positive trend	Match	Positive trend
2013/4	Negative trend	Match	Negative trend	Match	Negative trend
2013/5	Positive trend	Match	Negative trend	Match	Negative trend
2013/6	Positive trend	Match	Positive trend	Match	Positive trend
		6/6	Match	5/6	Match

Two months delay with Ifo index					
Date	Ifo index		Product Group		Product family 1
2012/12	Positive trend				
2013/1	Positive trend		Positive trend		Positive trend
2013/2	Positive trend	Match	Positive trend	No Match	Negative trend
2013/3	Negative trend	Match	Positive trend	Match	Positive trend
2013/4	Negative trend	No Match	Negative trend	No Match	Negative trend
2013/5	Positive trend	Match	Negative trend	Match	Negative trend
2013/6	Positive trend	No Match	Positive trend	No Match	Positive trend
		3/5	Match	2/5	Match

Three months delay with Ifo index					
Date	Ifo index		Product Group		Product family 1
2012/12	Positive trend				
2013/1	Positive trend		Positive trend		Positive trend
2013/2	Positive trend		Positive trend		Negative trend
2013/3	Negative trend	Match	Positive trend	Match	Positive trend
2013/4	Negative trend	No Match	Negative trend	No Match	Negative trend
2013/5	Positive trend	No Match	Negative trend	No Match	Negative trend
2013/6	Positive trend	No Match	Positive trend	No Match	Positive trend
		1/4	Match	1/4	Match

Figure 4.12 *The result of correlation analysis with Ifo index.*

The above figure shows the result of the correlation analysis between Ifo index and the sales data. These results indicate that there is a strong 6/6 one month delay correlation between product group and Ifo index. The results also show that there exist a 5/6 one month delay correlation between Ifo index and product family 1. The least correlation was three months delay.

Although there is a high correlation with two data series, this information is not fully reliably enough to be utilized with the case company's S&OP operations since the correlation analysis time frame was too narrow. However, one can determine from the global indexes that with the calculated probabilities the case company's business will behave in a similar way from trend perspective with one, two or three months delay. Therefore, one can create a sophisticated guess of the correlation predictability. Thus the case company can expect that correlation with trends exist between Ifo index, OECD index and the case company's sales data.

4.6 Quality control

Demand planning and forecasting requires KPIs. The key idea of forecast quality control is to improve the forecast and the demand plan accuracy. As the literature review introduced, there are several methods which should be utilized for the chosen forecasting method. For instance, the tracking signal, the forecast value adding line and the waterfall analysis. The need for creating the aforementioned KPIs is to provide fact-based high quality information to the case company's stakeholders, especially the participants of S&OP. The following sub chapters will introduce the methods in more detail.

4.6.1 Short term quality control

S&OP demand planning accuracy performance needs to be followed. Now that the forecasting method is chosen for the case company, one needs to set control limits to the forecast and also evaluate on a regular basis if the current forecast technique is valid for the historical sales data. Since there was no statistical forecasting made for demand planning in the past, the evaluation will be made to already complete demand plans. The current demand plan utilizes product family level. Thus the following results are based on product family 1. The literature review introduces, in chapter 2.4, a tracking signal method, which tells a user if corrections need to be made regarding the current forecast or demand plan. This tracking signal formula (19) uses mean absolute deviation as an input for forecasting data. However, one can also use MAPE. In this thesis MAPE is used, since it is more relevant to follow forecast accuracy than forecasting data from the case company's perspective. Therefore, demand plan accuracy is tracked instead of the behavior of the historical sales data. Regardless of the input, one need to set the upper and lower control limits. Although companies highly desire good forecast accuracy the levels should not to be set too high or too low. The problem for setting the limits to the aforementioned levels to the previously mentioned way is to avoid looking or overlooking the forecasts too often. The demand plan accuracy, showed in figure 4.13, for the latest available months are:

- 88.80 %, error is 11.20%
- 96.23 %, error is 3.77%
- 96.92 %, error is 3.08%
- 80.92%, error is 19.08%

Standard deviation of the errors is 6.49% and while it multiplied with the chosen safety factor 1.2 the control limits are 7.79 % from the maximum. Thus the precise upper control limit is 107.79 % and the precise lower control limit is 92.21 %.

For this analysis the chosen rounded limits are from 92 to 108 percentages and the plotted values are a ratio of product family 1 demand plan data and the actual sales figures.

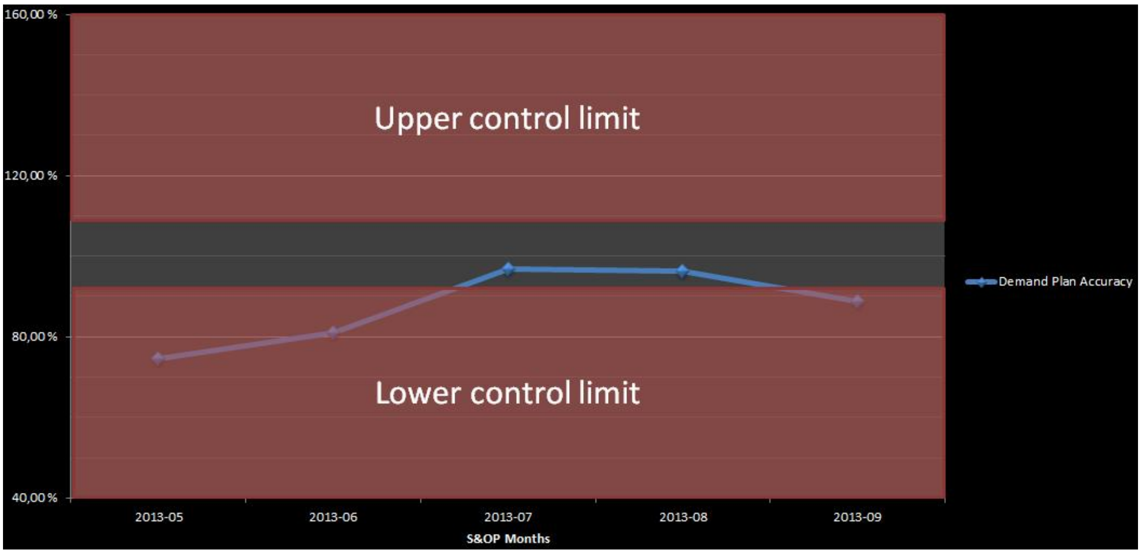

Figure 4.13 *The tracking signal for the case company's demand plan accuracy.*

Figure 4.13 illustrates a tracking signal for the short term forecast's forecasting accuracy. For instance, if the forecasting accuracy is below or above 8 percent of the 100% one needs to take action. As figure 4.13 shows the demand plan accuracy was below the lower control limit when S&OP process started. However, the current accuracy has improved but corrective actions may be needed since the accuracy is below the control limit. If, however, the accuracy constantly exceeds the limits, the regular behavior of the historical sales data has changed dramatically.

4.6.2 Forecast value adding line

Companies use forecasts as a tool to anticipate future events. Occasionally, however, forecasts are exceedingly complicated or sophisticated. To avoid low forecast accuracy, companies need to estimate if the current forecasting method is right for the data and how sophisticated the method should be. The literature review, in chapter 2.4, recommends that a forecast value adding line is a suitable technique to evaluate the current forecasting method from accuracy and data's volatility perspective. Additionally the aforementioned evaluation can work as a reference, especially when implementing new forecasting methods.

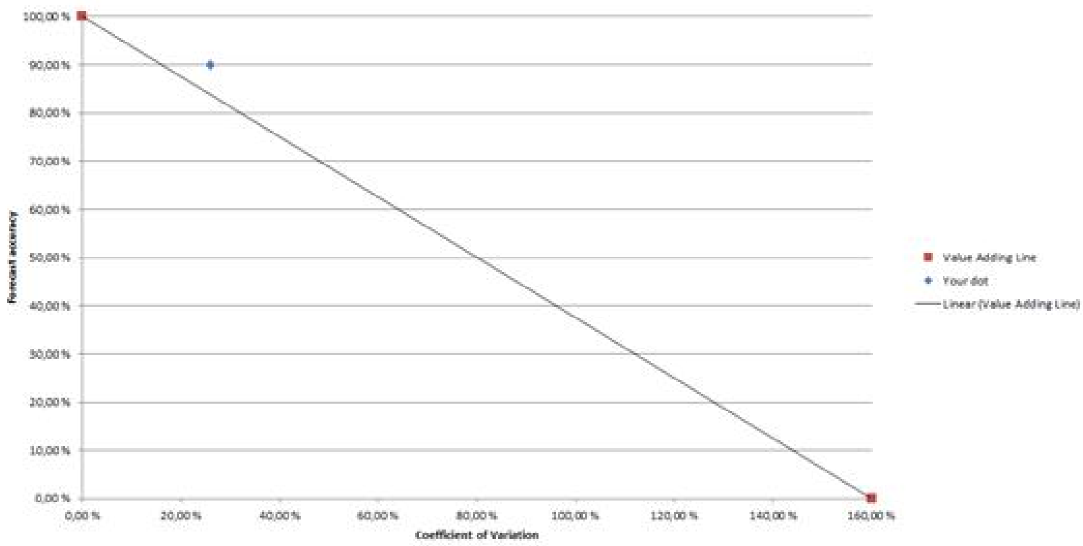

Figure 4.14 *Forecast value adding line for the chosen forecasting method.*

Figure 4.14 illustrates the forecast value adding line and the blue dot represents the Holt's-Winters' forecast. The long period forecasting error is roughly ten percent, as figure 4.8 shows, thus the accuracy is 90 percent and the volatility for product family 1's sales data is 25 percent as the calculated table 4.1 informs. As chapter 2.4 introduces, if the accuracy of the forecast will exceed a certain value, and on a graph the value is above the forecast value adding line, the current forecast should be conducted with a sophisticated forecasting method. If these conditions are not met, the forecasting method should be conducted with less sophisticated methods such as Moving averages, Trend projection or Naïve method. However in this case, the forecasting method is the most suitable according to the forecast evaluation and the above-presented analysis.

4.6.3 Long term quality control

Since the demand plan phase is an important part of S&OP process, it is highly important to also follow and control what was planned for long term and how well it performed with future demands. Therefore, one of the methods to conduct this is to create a waterfall analysis which will collect the historical plans and compare them with the actual figures when they are available.

ACCURACY WATERFALL

	2013-05	2013-06	2013-07	2013-08	2013-09	2013-10	2013-11	2013-12	2014-01	2014-02	2014-03	2014-04	2014-05
2013-05	74,63 %	80,92 %	73,36 %	78,07 %	78,92 %	80,04 %							
2013-06		80,92 %	73,36 %	78,07 %	78,92 %	80,04 %							
2013-07			96,92 %	95,30 %	85,65 %	99,26 %							
2013-08				96,23 %	90,04 %	111,14 %							
2013-09					88,80 %	97,42 %							
2013-10						104,21 %							
2013-11													

Figure 4.15 *The waterfall analysis for the demand plans of the product family 1.*

Figure 4.15 illustrates the waterfall analysis. It will collect the data from each S&OP month. Eventually, when S&OP is mature enough, it will inform the uncertainty of each planned S&OP month in to the future. With this knowledge the case company has an opportunity to make plans for operations side, such as inventory optimization and material purchasing utilizing the demand plan and the expected uncertainty. For example the demand plan being constantly ten percent off from the actual sales, the case company can plan future purchasing and production by not trying to match the demand, instead, trying to match the demand after being reduced by ten percent. This way the case company has a high potential to improve competitiveness.

4.7 Summary of the results

The case company's products have been categorized with the ABC/XYZ analysis using the lowest hierarchy level. The results indicate that approximately ten percent of products of each product families belong to a good forecastability group - AX products. The majority, however, are Z products which have high volatility and thus hard to forecast. The rest of the products belong to the group marked as yellow, which requires a decision from the case company either to include them to the statistical forecasting process or to build a safety stock for these products along with Z and C products.

The key finding of the statistical forecasting test was the chosen method for the case company. Holt's-Winters' method had the best forecast accuracy in the long term accuracy test and in the short term accuracy test. Since the case company desired to weigh forecasting accuracy more than other attributes of the test, the result clearly shows that the aforementioned method is the most suitable for the case company's sales data.

The correlation analysis discovered that there is a strong correlation between Ifo index and the case company. The correlation analysis used trends for comparison and one month delay proved to be the strongest. Although a correlation was found, the time frame was too narrow to confirm that there is a full correlation.

Quality control was built to constantly evaluate the forecast and the demand plan accuracy in the case company. Quality control utilizes short and long term forecast accuracy measurements and the forecast value adding line to determine the suitability of the current forecasting method. Short term accuracy measurements use low and high control limits to inform the case company if the sales data has dramatically changed. Thus, the case company can change the current forecasting method. The purpose of the forecast value adding line is to inform the case company of the suitability of the current forecasting method for forecasting. In other words it recognizes if the current forecasting method is too sophisticated or too non-sophisticated. Long term quality control utilizes the waterfall analysis to collect the historical demand plans or forecasts and actual figures. The purpose of the analysis is to compare the plans and actual figures together and evaluate the accuracy. With this analysis the case company can recognize the future periods expected forecast error.

5 DISCUSSION OF THE RESULTS

Since forecasts remain the backbone of the S&OP demand plan, it is important to choose the right statistical forecasting method for specific data. The forecasts can be used, for instance, for purchasing materials beforehand to match the demand and in the end balancing supply and demand. This will result in a better service level. All in all, forecasts enable companies to anticipate the future and steer the SCM to meet the requirements of the demand. The reason why to do all this is simple. Competitive companies need to conduct sustainable business and provide service to customers in order to profit. Therefore, inventories and material purchasing need to work in a cost effective way. S&OP among forecasts grant an opportunity to conduct this kind of business.

Despite the fact that statistical forecasting is one key input of the demand plan process, the importance of qualitative methods cannot be ignored. Since the focus of this thesis was to discover the best statistical forecasting method for the case company's business, the chosen statistical forecasting method is lacking human intuitions and assumptions. According to the literature review, the most sophisticated forecasting methods include human intuitions as a part of the forecasting process. Additionally including qualitative methods to the statistical forecasting process increases the forecast accuracy. Although a qualitative method could rise the accuracy level there are difficulties to conduct these methods since S&OP has a tight schedule and most often qualitative methods create a survey which will take a few of days to complete. Therefore, qualitative methods could be used for assessment, for example, for new product launches or to evaluate new market fields. Although the literature review states that combining the qualitative and the quantitative methods in statistical forecasting process increase the forecast accuracy, the case company currently uses both methods while doing demand planning. Therefore, one can leave out the qualitative method from the statistical forecasting process.

The quantity of the data for the empirical part of the thesis was barely sufficient. The forecast analysis would be more conclusive if there would be at least four or five full years of data available. That would enable better parameter optimization by minimizing MAPE value due to the reason that MAPE is better for inventory and capacity planning. The optimization could be conducted by minimizing another error such as mean forecast error if, however, the purpose of the statistical forecasting is to optimize material planning. Nonetheless, the analysis of the data was adequate enough to find a suitable method. The analysis as well as conducting forecasting proceeded as figure 3.2 illustrated. The results of the analysis were outstanding. With the aid of the results some of the statistical forecasting methods were excluded from the forecasting tests. These exclusions were conducted solely based on the literature review. Using the knowledge of the literature review, the remaining statistical forecasting methods were analyzed. Based on the different level of sophistication, the six were chosen for the tests.

According to the literature review, an important step to improve forecasting is to clean the data to reduce the forecast error. In other words the data needs to be analyzed, studied and organized before entering it to forecasting phase. In practice ABC/XYZ analysis can be conducted to find which products have high monetary importance and low variability. This enables forecast accuracy to increase as well as the forecast covers only the high interest products instead of covering all products. Although the literature recommends that BX and AY products are good for forecasting, the case company's S&OP forecasting maturity is not currently good enough to add Y products to the statistical forecasting process. However, BX products can be forecasted if the case company wants to include these products to forecasting process. Therefore, the researcher's opinion is to mark AX products as the easily forecastable products. The literature supports the discovery that forecasting gets harder when the time frame gets shorter and the product hierarchy grows in depth. Furthermore the volatility of other product hierarchies are more stable, thus the forecasting tests needs to be conducted at one of those levels. It is important to understand and manage the volatility of the product hierarchy in order to conduct statistical forecasting in the future when the case company has a capability to expand the range of forecasting to the lowest product hierarchy.

The chosen six forecasting methods utilized the product group hierarchy in the tests. The results were promising due to the reason that the forecast errors were not too big. In addition the results support the previous findings in the literature review. For instance Naïve forecasting method is not reliable when conducting long period forecasting. The historical sales data has a trend and seasonality behavior, as they were discovered in chapter 4.1, which supports the selection of Holt's-Winters' three parameter method which is the most suitable method for this kind of data according to the literature review. During this research the test compared six different statistical forecasting methods with five recommended attributes which are introduced in chapter 3.2. It is obvious that the results could change if the tests would be redone, since some of the results of the common attributes, such as costs and usability are subjective. Therefore it can be assumed that another researcher with a similar skillset would have relatively same results. Nevertheless the accuracy tests remain the same which will correspond with the literature review. The stress for the common attributes and forecast accuracy were chosen by the case company's interest for having a reliable forecasting method. This refers to good forecast accuracy. The case company has chosen to stress the forecast accuracy more than common attributes. However, it is possible to change the stress values if interest towards common attributes changes. Based on the results and the stress, the chosen statistical method was Holt's-Winters'.

While conducting the correlation analysis the scope was limited to six months due to the reason that the historical sales data was the most reliable during that period of time. Additionally the product's data was limited to Europe due to the above reason and since the Ifo standards are made for Germany. Another correlation source was OECD index. The idea behind this limitation was to match the demand area with Ifo and OECD indexes with valid data. Since the case company and these global indexes uses different data, they cannot be directly compared together. The correlation analysis used trends based on a monthly change. Thus these changes are positive, negative or no change. Since it was important for the case company to understand if their data follows the global indexes the delays were used only for the case company's data. The findings of the correlation analysis show that only one strong correlation was discovered by one month delay with Ifo index. Although the target was to find a correlation or to determine that correlation does not exist, the correlation with one month delay did not fully satisfy since the time period was too narrow. Despite the limitations, the results were promising and clearly corresponded with the literature review that companies operating worldwide are entangled together. Thus the correlation analysis should continue beyond this time frame to determine how strong the correlation is during long time periods.

Forecasting and the historical data play a high role when conducting S&OP. Although current forecasts are reliable, sudden changes with the data might happen which would alter the behavior of the sales data. For instance a company can start to sell new products or dramatically lose a market share. After these changes the current statistical forecasting method would give inaccurate results due to the behavior of the data. According to the literature review a tracking signal is useful technique to recognize these data behaviors. Though, the literature review bestows that a tracking signal should use MAD (20) formula as the parameters, the tracking signal in this thesis, however, consists of time and forecast error parameter. This way one can track the accuracy as well as the behavior of the data when utilizing the forecast value adding line in to the evaluation equation. Although the parameters have changed the main idea behind the tracking signal remains the same. The tracking signal uses control limits to inform if the data or forecast accuracy has dramatically changed. In this thesis these limits are calculated using standard deviation. The source is demand plan accuracy of the four latest available demand plan months. The reason for choosing this method was to ensure that relevant changes are noted when they occur based on the fact that the case company wants to have a high service level. Yet to ensure that the data is not checked too often the calculated figure is multiplied with a 1.2 safety factor. In the future if the safety factor is too low and the forecasts are checked too often, it needs to be changed to a bigger value.

The case company presented three research questions which were the targets of the research. The questions are:

- How to analyze and categorize and forecast different products in the case company's business globally?
- How to link above-mentioned into the S&OP framework?
- How to utilize further for operations?

The answer to the first question was in ABC/XYZ analysis and forecasting method tests. This ABC/XYZ analysis categorizes the case company's products by their forecastability. Also the aforementioned analysis will recognize products which can be included to the forecast process by product's monetary importance and volatility. Regarding the rest of the products, the case company can decide either to keep a safety stock or to remove the stock profile if the monetary importance is not great. The forecasting tests discovered the most suitable method to the case company's sales data. The tests compare six different forecasting methods using MAPE as a parameter.

The answer to the second question is to start to use statistical forecasting as a part of the S&OP process. The statistical forecasting will give support to the makers of the demand plan and the selected forecasting method will give fact-based information of the future. The statistical forecasting enables the case company to adjust production and inventory levels to match the desired service level. Additionally, the results give S&OP an opportunity to exclude high volatility products off of the statistical forecasting process.

The answer to the third question relates, for instance, to material purchasing or capacity planning. Since forecasts allow the case company to anticipate the future, the material purchasing or capacity planning can also be conducted more accurately for those low volatility products which are included in the forecasting process if forecasting is done for the lowest product hierarchy level. Furthermore, the waterfall analysis will anticipate the expected future error when the S&OP maturity is good enough in the case company. This knowledge enables the case company to make right decisions to adjust supply to match real demand. In addition, the demand plan, statistical forecasting included, will improve operations dramatically. Even though sales will have more new and permanent customers because of the better service level, the operations side will benefit having reduced inventories and inventory costs. Especially turnover time will decrease because of more optimized production and more conclusive understanding of the demand. The most important improvement for the operations is higher flexibility because the demand plan accuracy is high thus it will enable production units to anticipate the future well in advance.

6 CONCLUSIONS

The focus of the thesis was to analyze, categorize different products and to discover the most suitable statistical forecasting method for the case company's S&OP demand planning. Although the key challenge was to find a good forecasting method, it turned out to be an analysis of the historical sales data. The data analysis plays a key role during the research. One of the main findings was that any data is not good enough for statistical forecasting. Due to that reason, there was a need to analyze and categorize the historical sales data. In order to conduct forecast simulations, the data was evaluated by creating a graph which would show how the data behaved during the time. The purpose of this pre-analysis was to find information, for example trends and seasonality, and to exclude some forecasting methods from the forecasting analysis according to the finding. The reason for this was to avoid adding similar forecasting methods to the simulations.

S&OP demand planning phase requires a forecast as an input. A statistical forecast most often is a good start for the demand planning round, since it is considered to be reliable for its statistical approach to sales figures. The output of the statistical forecast will be the base for demand planning and enable fact-based production planning and inventory optimization. Aforementioned analysis compared forecasting methods together evaluating their, among others, forecasting accuracy. The comparison of the six different forecasting methods resulted in one suitable method. For the selected data the most suitable forecasting method was Holt's-Winters', although all of these tested forecasting methods had a good score. Nevertheless Holt's-Winters' method had the ability get the highest score.

When the output of Holt's-Winters' forecasting method is studied, the results indicate that the forecast and the historical sales data shared approximately the same coefficient of variation. The reason for this phenomenon is that the forecasting method mimics the behavior of the historical sales data. This is a one good indicator that the forecast is realistic and reliable from accuracy perspective.

This thesis discovered a lot of relevant information which is important for the statistical forecasting. For instance, the importance of low volatility of the data. The data was categorized by using ABC/XYZ analysis. This analysis sorts the products by their volatility and monetary importance. The need for conduct this categorization was to understand which kind of products can be putted in to the statistical forecasting process while conducting more detailed forecasting. The reason for the categorization is to improve the forecast accuracy. The output of the categorization will increase the case company's understanding which products should be forecasted in the demand planning process. In addition the analysis reveals products which have high monetary value.

The most important task of forecasting is a holistic study of the behavior of the sales data. One needs to evaluate if the data is good enough for forecasting. One of the good indicators is to make an ABC analysis for the products and to find the high value products. Regardless of the fact that a company's service level is desired to have a high value, forecasting should at least include those products which have a high value to the company. Second indicator for forecasting is calculating XYZ analysis. XYZ analysis calculates coefficient of variation for each product which is about to be forecasted. This calculation's output is products which can be forecasted and which are hard to forecast. X products have low variability thus these are easy to forecast, Y products have medium variability and Z products have high variability therefore they are hard to forecast. After these two analyses one can choose products which will give a reliable forecast for high value products.

The correlation analysis discovered that there exist a correlation between Ifo index and the historical sales data of the case company when comparing monthly trends. The correlation was the strongest with one month delay. For the demand planning purposes, knowing that the correlation exists, one can expect a similar trend behavior in the central Europe area. Since, the Ifo data covers Germany area and the case company's data were limited to cover only Europe's historical sales data.

6.1 Recommended actions

The case company now recognizes which products are low in variability and high in monetary importance within the four product families. This information can be utilized further as a part to S&OP operations by, for instance, purchasing components to these products using demand forecasts. Additionally the case company can keep a safety stock for those products which are harder to forecast. Usually these are Z products. The reason for doing this is to keep the case company's service level high. Following figure 6.1 illustrates the how the safety stocks become more relevant while monetary value decreases and volatility increases.

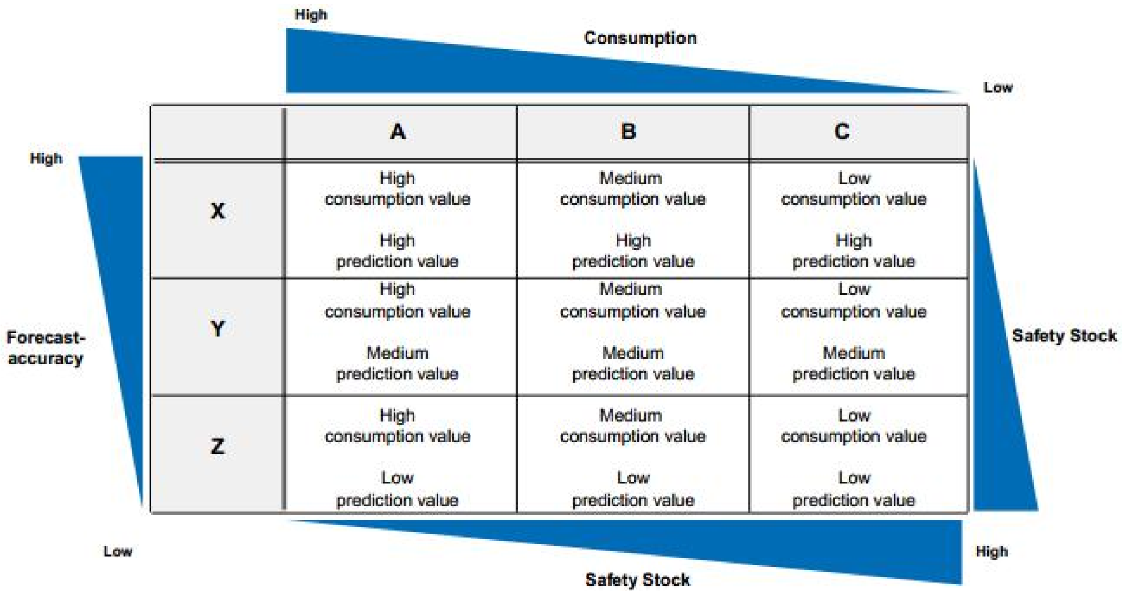

Figure 6.1 *The ABC/XYZ matrix* [66].

As figure 6.1 points out AX products value and forecast accuracy are high. Thus the case company has an opportunity to meet the demand by anticipating the future, for instance purchasing components relying on the forecasts. In other words the purchasing process for AX products could be conducted by utilizing S&OP demand plan instead of making a sophisticated guess. This approach would increase costs and temporarily material inventory will increase, however it would also increase service level. Another option is to change production of the AX products towards the demand plan figures which utilizes the statistical forecasting as an input. This option would make the supply chain more agile since above products' demand is stable.

The uncertainty of S&OP demand plan would be well known when the case company's S&OP maturity is good enough. This uncertainty can be followed by using the waterfall analysis. The action from the case company's side is to decide which products from ABC/XYZ analysis are important for the forecasting process or keep the process more aggregate level.

The results of the forecasting method analysis indicates that the most suitable forecasting method is Holt's-Winters' for the case company's sales data. Now the case company could start to utilize statistical forecasting as a part of the S&OP process to support the persons making of the demand plan. If the method is not resulting to adequate forecast accuracy, the data is needed to reanalyze or the forecasting method needs to be changed. A good indicator when to conduct these actions is to use forecast value adding line as a KPI for forecasting. Additionally, the waterfall analysis gives an opportunity to calculate the expected error in the future demand plan. This information, in figure 6.2, bestows the case company to adjust the operations plans to match the adjusted demand, if the demand plan is always off the target with some percentage. These figures are calculated using forecast error values from the waterfall analysis in figure 4.15 as follows.

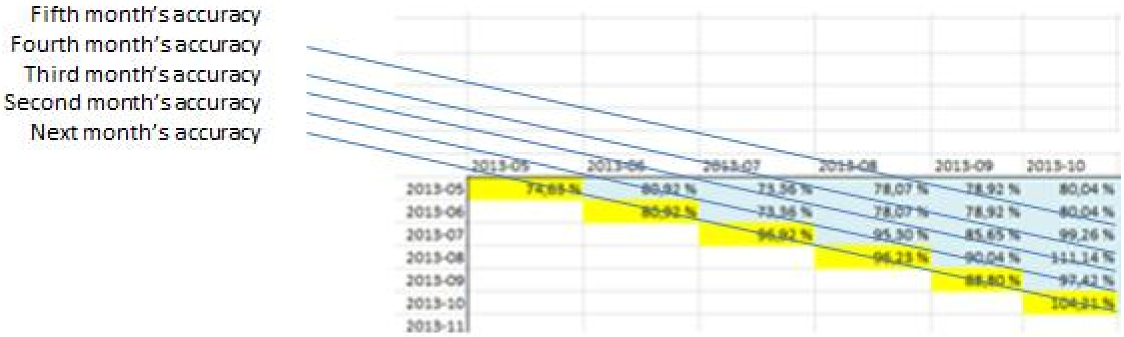

Figure 6.2 *The data for calculation of the expected error.*

The figure 6.2 shows the data which is utilized with the expected error calculation. From these figures an average is calculated and that value is used to create an expected error for the future demand plan rounds. The last value is not used in the expect error calculation, since there are only one demand plan error available.

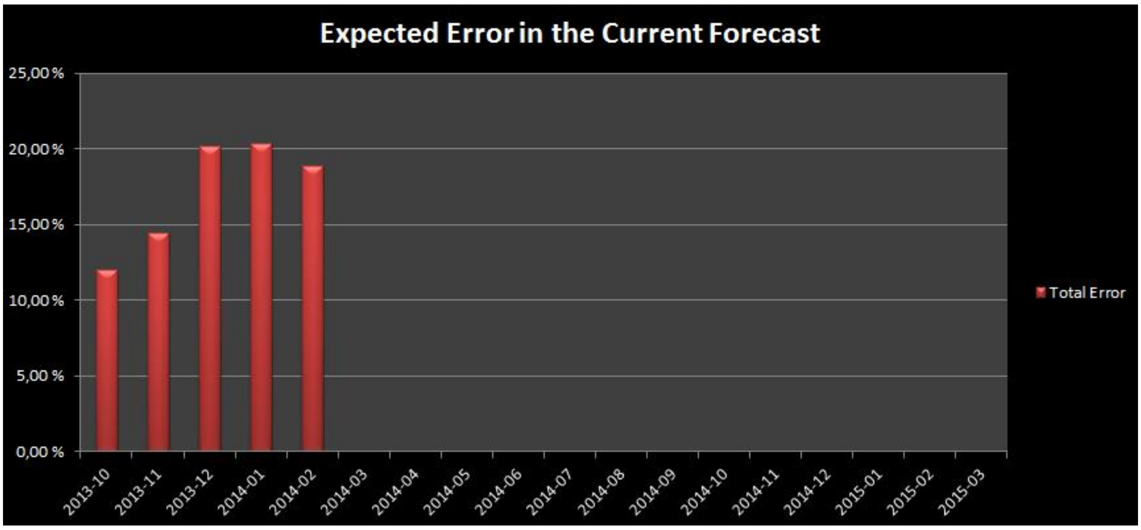

Figure 6.3 *Expected error in the future demand plan.*

Since S&OP is new process in the case company, there are only few completed S&OP rounds. Therefore the information about the expected errors for all future months inside the S&OP time frame are not available until the case company's S&OP process is 18 months old. However, the expected error, presented in the figure, for few future months is available.

The case company should start to follow correlation between Ifo and the sales data. If the correlation is constantly strong, the case company can use that information as a decision making tool to adjust demand plans and production. For instance, the demand plan should have the same trend behavior as the Ifo index with one month delay.

6.2 Further research opportunities

The scope was global for this thesis; however this research was highly limited with the selected products. A good further research could cover several other products which the thesis did not have in the scope. The most interesting further research topic could be uncertainty in long period forecasting and how that information could be utilize in S&OP. Obviously, the near future forecasts have a better accuracy than the one which will project the future one year ahead. Since it is easy to evaluate the current accuracy level by using MAPE or some commonly known accuracy formulas, the uncertainty tend to inherit from the forecast made recently. Waterfall analysis of the forecasts is one of the practical methods which can keep a track how did the forecast changed during the time, however companies which are commencing their forecasting do not have a long historical forecast values available. Therefore a future research could try to find mathematical formulas or algorithms to recognize uncertainty for specific data series and utilize this information to the case company S&OP process.

Aggregated forecasts comparing to disaggregated forecasts combined into one forecast are considered to be more accurate. In many empirical studies disaggregate forecasts combined into one aggregate forecast have a better forecast result. Therefore it is clearly a good opportunity to study several individual products' statistical behavior and to create several forecasts. After this one should measure how much the accuracy will improve when the aforementioned forecasts are combined together to from an aggregate forecast. As chapter 2.4 introduced that some forecasts are more accurate if aggregation is done for short or medium forecasts. This would be beneficial for the case company's statistical forecasting process if forecast accuracy could be improved.

Additionally one potential research opportunity is to find how well the demand plan forecasting aids the operations side of S&OP. Particularly, if the AX products material purchasing is conducted as the subchapter 7.1 introduced.

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Huttunen S. Business Development Manager, Case Company. Interview 17.6.2013

Haatainen V. S&OP Project Manager, Case Company. Interview 1.8.2013

Pohjalainen J. SCM Manager, Case Company, Interview 2.8.2013

APPENDICES

Appendix 1. Mathematical formulas for forecasting [1, 46]

Naïve:

$F_{t+1} = D_t$, where (2)

F_{t+1} Is the forecast for the next period of time

D_t Is the demand for the current period of time

Trend projection:

$b = \frac{\sum xy - n\dot{x}\dot{y}}{\sum x^2 - n\dot{x}^2}$, where (3)

b is slope of the regression line

x is known values of the independent variable

y is known values of the dependent variable

ẋ is average of the x-values

ẏ is average of the y-values

n is number of data points or observations

Moving averages:

$F_t = MA_n = \frac{\sum_{i=1}^{n} A_{t-i}}{n}$, where (4)

F_t is the forecast for the next period of time

i is an index that corresponds to period of time

A is average for time period t

MA is Moving averages

F_t is Forecast for time period t

Single Exponential Smoothing:

$F_{t+1} = F_t + \alpha(D_t - F_t)$, where (5)

F_{t+1} is the forecast for the next period of time

D_t is the demand for the current period of time

F_t is Forecast for time period t

α is exponential smoothing constant

Holt's two parameters method:

$L_t = \alpha D_t + (1-\alpha)(L_{t-1} + b_{t-1})$ (6)
$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$ (7)
$F_{t+m} = L_t + b_t m$, where (8)
L_t is estimate of the level of the series at time t
b_t is estimate of the slope of the data series at time t
D_t is the demand for the current period of time
α is exponential smoothing constant
β is exponential smoothing constant
m is number periods in one cycle (for a year it is 12 months)

Holt's-Winters' three parameter method:

$F_t = \alpha \frac{D_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1})$ (9)
$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$ (10)
$S_t = \gamma \frac{D_t}{L_t} + (1-\gamma)S_{t-s}$ (11)
$F_{t+m} = (L_t + b_t m)S_{t-s+m}$, where (12)
s is season's length
L_t is an estimate of the level of the series at time t
b_t is an estimate of the slope of the data series at time t
D_t is the demand for the current period of time
S_t is Seasonal component
b_t is estimate of the slope of the data series at time t
m is number periods in one cycle (for a year it is 12 months)
α is exponential smoothing constant
β is exponential smoothing constant
γ is exponential smoothing constant

Browns method:

$$F_{t+1} = S_{t+1} + T_{t+1} \quad (13)$$
$$S_{t+1} = \alpha_B D_t + (1 - \alpha_B) * (S_t + T_t) \quad (14)$$
$$T_{t+1} = \beta_B (S_{t+1} - S_t) + (1 - \beta_B) T_t \quad (15)$$
$$\alpha_B = 1 - (1 - \alpha)^2 \quad (16)$$
$$\beta_B = \frac{\alpha^2}{1-(1-\alpha)^2} \text{, where} \quad (17)$$

$0 \leq \alpha \leq 1$ is a smoothing parameter

D_t is the demand for the current period of time

S_t is Seasonal component

T_t is Trend component

Bayesian:

$$F = \frac{Moving\ Averages}{4} + \frac{Holts'Winter's}{4} + \frac{Trend\ projection}{4} + \frac{Brown's}{4} \quad (18)$$

Appendix 2. Mathematical formulas for error measuring [1]

Tracking signal:

$$Tracking\ signal\ =\ \frac{RSFE}{MAD} = \frac{\sum(Actual\ demand\ in\ period\ i - Forecast\ demand\ in\ period\ i)}{\frac{\sum|Actual - Forecast|}{n}} \quad (19)$$

Mean absolute deviation (MAD):

$$MAD\ = \frac{\sum|Actual - Forecast|}{n} \quad (20)$$

Running sum of forecast errors (RSFE):

RSFE = $\sum(Actual\ demand\ in\ period\ i - Forecast\ demand\ in\ period\ i)$ (21)

Mean absolute percentage error (MAPE):

$$MAPE\ =\ \frac{\sum_{t=1}^{n}\left|\frac{Forecast\ error\ for\ time\ period\ t}{Actual\ demand\ for\ period\ t} * 100\%\right|}{n} \quad (22)$$

Mean forecast error (MFE):

$$MFE\ =\ \frac{\sum_{t=1}^{n}\frac{Forecast\ error\ for\ time\ period\ t}{Actual\ demand\ for\ period\ t}}{n} \quad (23)$$

Appendix 3. Variability figure of the product group products